The Economics of Alcohol

A Collection of Essays

by

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Declaration

I hereby declare that this thesis is my own work and has not been submitted in any form for the award of a higher degree elsewhere.

Acknowlegements

I am grateful to many people who have, over the course of my PhD, helped in numerous ways.

Firstly, I am grateful to my supervisors Ian Walker and Bruce Hollingsworth. They are both always ready and willing to help with any problem, or discuss any idea with me. They have helped shape not only this thesis, but also helped shape me as an academic researcher and health economist. Both have accompanied me on conferences, been encouraging supervisors and introduced me to many potential collaborators. As an early career researcher I think myself lucky to have found two such generous and helpful supervisors, and couldn't ask for better role models. I am also grateful to the many members of the department who have helped with insightful comments and questions about my work. I am also grateful to all the participants at conferences where I have presented my work, especially Anne Ludbrook and Paula Lorgelly who have been my discussants at the Health Economists' Study Group and whose comments have helped strengthen my work.

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Last but certainly not least, I wish to thank my family for all their love and support; their constant encouragement has helped endlessly. I am especially grateful to my wife Sarah, who has never failed to support me throughout my PhD and even agreed to marry me during the course of my studies.

The Economics of Alcohol: A Collection of Essays

by Robert Ewan Pryce, BA MSc

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Abstract

This thesis consists of three self-contained essays on the economics of alcohol demand.

Chapter 2 examines the price elasticity of demand for alcohol across the drinking distribution, using household expenditure data to test whether heavy drinkers respond the same as light drinkers to price increases. Both conditional and unconditional quantile regression are used to compare results generated by the two different methods. The chapter finds that when price increases, heavier drinkers decrease consumption proportionately less than lighter drinkers whilst substituting more towards lower quality beverages. This is an important result since it shows that price-based policies may have little effect in reducing heavy consumption whilst creating large welfare losses for moderate drinkers.

Chapter 3 uses several different methods including the Tobit and Double-Hurdle models to estimate the mean price elasticity of demand for alcohol. In doing so, it tests how the price elasticity estimates can differ depending on model choice, even when the same data is used. Household expenditure data contains a large number of households who do not purchase any alcohol, for three distinct reasons: price reasons, non-price reasons, and infrequent purchase. A double-hurdle model is developed which can accommodate all three types of non-purchase. The results suggest that, compared to the double-hurdle model, the frequently-used Tobit model produces larger absolute estimates of the price

elasticity of demand for alcohol. The double-hurdle model is the prefered specification since it incorporates all reasons for zeros in alcohol expenditure.

Chapter 4 explores changes in alcohol consumption across the lifecourse using a large number of waves of a cross-sectional survey, the General Household Survey, to create synthetic cohorts. Whilst the existing literature looks at how the *mean* consumption differs across birth cohorts, this chapter instead looks at different quantiles of the drinking distribution to examine whether the changes are consistent across all drinkers, including abstention. This is important because it shows how the alcohol consumption distribution has changed across time, age and birth cohort. It finds that generally, alcohol consumption decreases both as age increases and in older birth cohorts. Alcohol consumption by females has particularly changed; younger birth cohorts drinking much more than their parents' cohorts did, yet younger birth cohorts are also more likely not to drink at all.

Whilst these chapters can be considered stand-alone essays, they are also linked and show how different and cutting edge techniques, applied to the best available data, can be used to show new and interesting results which can aid policymakers and policy decisions.

Notes

This PhD has been funded by the Economic and Social Research Council. The project was granted ethical approval by the Faculty of Health and Medicine Research Ethics Committee. Proof of approval is provided in Appendix A.

References for this thesis are combined, rather than stated at the end of every chapter, and can be found at the end of this thesis.

Chapter Two has been presented at the Health Economists' Study Group (HESG) 2015 meeting in Lancaster. A very early version of Chapter Three, without the quality element, was presented at the HESG 2014 meeting in Sheffield. A full version of the chapter was presented at the North West Doctoral Training Centre (NWDTC) 2015 conference in Manchester and the International Health Economics Association (iHEA) 2015 meeting in Milan.

Data used is provided mostly by the UK Data Service and the Office for National Statistics, who bear no responsibility for the analysis or interpretation.

Contents

Acknowledgements **i**

Abstract **iii**

Notes **v**

Contents **vi**

List of Figures **x**

List of Tables **xii**

1 Introduction **1**

1.1 General Background 1

1.1.1 Alcohol - An Overview 1

1.1.2 Why Drinking Matters 4

1.1.3 Alcohol and Externalities 6

1.1.4 Alcohol Policy 7

1.1.5 Alcohol, Prices and Taxation 9

1.2 Motivation and Aims 13

1.3 Structure and Content 14

1.3.1 Brief Overview of Chapter 2 14

1.3.2 Brief Overview of Chapter 3 14
1.3.3 Brief Overview of Chapter 4 15

2 Quality or Quantity? The Differing Response to Price Changes across the Drinking Distribution 16

2.1 Introduction 16
2.2 Literature Review 19
2.2.1 Quantity Response across the Drinking Distribution 19
2.2.2 Quantity Response for Different Goods 23
2.2.3 Quality Literature 24
2.3 Data 26
2.3.1 Summary Statistics 27
2.4 Methods 30
2.4.1 Quantity 30
2.4.1.1 Conditional Quantile Regression 31
2.4.1.2 Unconditional Quantile Regression 32
2.4.2 Quality and Unit Prices 33
2.5 Results 35
2.5.1 Quantity - Conditional Quantile Regression 35
2.5.2 Quantity - Unconditional Quantile Regression 42
2.5.3 Quality 44
2.6 Discussion 47
2.6.1 Implications for Minimum Pricing 47
2.6.2 Limitations of the Study 49
2.6.3 Robustness Checks 50
2.6.4 Future Work 51
2.7 Conclusions 52

3 The Demand for Alcohol: A Double-Hurdle Model with Abstention and Infrequency 53

3.1 Introduction 53
3.2 Literature Review 54
3.2.1 Alcohol Demand 54
3.2.2 Zeros in the Dependent Variable 58
3.3 Methods 61
3.3.1 Unconditional OLS 61
3.3.2 Conditional OLS 61
3.3.3 Tobit Model 62
3.3.4 P-Tobit Model 62
3.3.5 The Double-Hurdle Model 63
3.3.6 Variables 64
3.4 Data and Summary Statistics 65
3.5 Results 70
3.5.1 Unconditional OLS 70
3.5.2 Conditional OLS 70
3.5.3 Tobit Model 71
3.5.4 P-Tobit Model 75
3.5.4.1 P-Tobit Marginal Effects 77
3.5.5 Double-Hurdle Model 77
3.5.5.1 Double-Hurdle Marginal Effects 80
3.6 Conclusion 80
3.6.1 Limitations and Future Research 80

4 Heavy Drinking and the Life Course: A Synthetic Cohort Analysis 82
4.1 Introduction 82
4.2 Literature Review 84
4.2.1 Drinking and the Life Course 84
4.2.1.1 Kemm (2003) 84
4.2.1.2 Meng et al (2014b) 86
4.2.2 Rational Addiction 87

4.3 Data and Methods 88
4.3.1 Data 88
4.3.2 Methods 89
4.3.2.1 Possible Methodological Limitations 92
4.4 Results 93
4.4.1 Quantile Extension of Kemm (2003) 93
4.4.2 Quantile Extension of Meng et al (2014b) 101
4.4.3 Age-Period-Price Results 121
4.4.4 Rational Addiction Framework 123
4.5 Conclusions 124
4.5.1 Future Research 126
5 Concluding Remarks **128**
6 Bibliography **131**
7 Appendices **147**
Appendix A - Ethics Clearance 147
Appendix B - Simulation: Selection by Dependent Variable 149

List of Figures

1.1 Mean Alcohol Consumption within OECD 2
1.2 Alcohol Consumption over Time: A Comparison 2
1.3 Alcohol Consumption over Time: Breakdown by Drink Type 3
1.4 Alcohol Duty as a Percentage of Total Tax Revenue 4
1.5 UK Duty Rates by Drink Type and Strength 10
1.6 Duty per Hectolitre of Beer 11
1.7 Duty per Hectolitre of Wine 11
1.8 Duty per Hectolitre of Spirits 12

2.1 Drinker Group Distribution from GHS 2006 22
2.2 Estimated Per-Capita Weekly Units 28
2.3 Real Price per Unit Paid by Drinking Quintile 29
2.4 On- and Off-Premise Units by Drinking Quintile 29
2.5 Alcohol Prices over Time 30
2.6 Price Elasticity of Quantity Demanded: All Alcohol 40
2.7 Price Elasticity of Quantity Demanded: On-Premise Alcohol 40
2.8 Price Elasticity of Quantity Demanded: Off-Premise Alcohol 41
2.9 Price Elasticity of Quantity Demanded: All Alcohol 44
2.10 Price Elasticity of Quality Demanded 46
2.11 Price Elasticity of Demand: All Alcohol 46

3.1 Fortnightly Expenditure on Alcohol, by Household 66

4.1 Long Term Real Price of Alcohol 83
4.2 Abstention - Male 95
4.3 Abstention - Female 95
4.4 Over Guidelines (Kemm's 'Heavy Drinkers') - Male 96
4.5 Over Guidelines (Kemm's 'Heavy Drinkers') - Female 96
4.6 Lower Quartile - Male 97
4.7 Lower Quartile - Female 97
4.8 Median - Male 98
4.9 Median - Female 98
4.10 Upper Quartile - Male 99
4.11 Upper Quartile - Female 99
4.12 90th Percentile - Male 100
4.13 90th Percentile - Female 100
4.14 Lower Quartile APC: Male 111
4.15 Median APC: Male 112
4.16 Upper Quartile APC: Male 113
4.17 90th Percentile APC: Male 114
4.18 Lower Quartile APC: Female 115
4.19 Median APC: Female 116
4.20 Upper Quartile APC: Female 117
4.21 90th Percentile APC: Female 118
4.22 All Quantiles: Male 119
4.23 All Quantiles: Female 120

7.1 Scatterplot of Y against x_1 and x_2 150

List of Tables

2.1 Summary Statistics 28
2.2 Price Elasticity of Quantity Demanded: All Alcohol 37
2.3 Price Elasticity of Quantity Demanded: On-Premise Alcohol 38
2.4 Price Elasticity of Quantity Demanded: Off-Premise Alcohol 39
2.5 Price Elasticity of Quantity Demanded: All Alcohol 43
2.6 Comparison of Conditional and Unconditional Quantile Regressions . . 43
2.7 Price Elasticity of Quality Demanded: All Alcohol 45

3.1 Summary Statistics 69
3.2 Outcomes by Household Type 69
3.3 Unconditional OLS 72
3.4 Conditional OLS 73
3.5 Tobit Model 74
3.6 p-Tobit 76
3.7 P-Tobit Marginal Effects 77
3.8 Double-Hurdle Model 79
3.9 Double Hurdle Marginal Effects 80

4.1 Birth Cohort Definitions 90
4.2 Age Band Definitions 91
4.3 Negative Binomial Results - Age Coefficients 102

4.4 Negative Binomial Results - Period Coefficients 103
4.5 Negative Binomial Results - Cohort Coefficients 104
4.6 Quantile Regression - Male - Age 105
4.7 Quantile Regression - Male - Period 106
4.8 Quantile Regression - Male - Cohort 107
4.9 Quantile Regression - Female - Age 108
4.10 Quantile Regression - Female - Period 109
4.11 Quantile Regression - Female - Cohort 110
4.12 Age-Period-Price Regression Results 122
4.13 Rational Addiction Model - Collapsed at Quantiles 124

7.1 Comparison of Estimated Coefficients 150

Chapter 1

Introduction

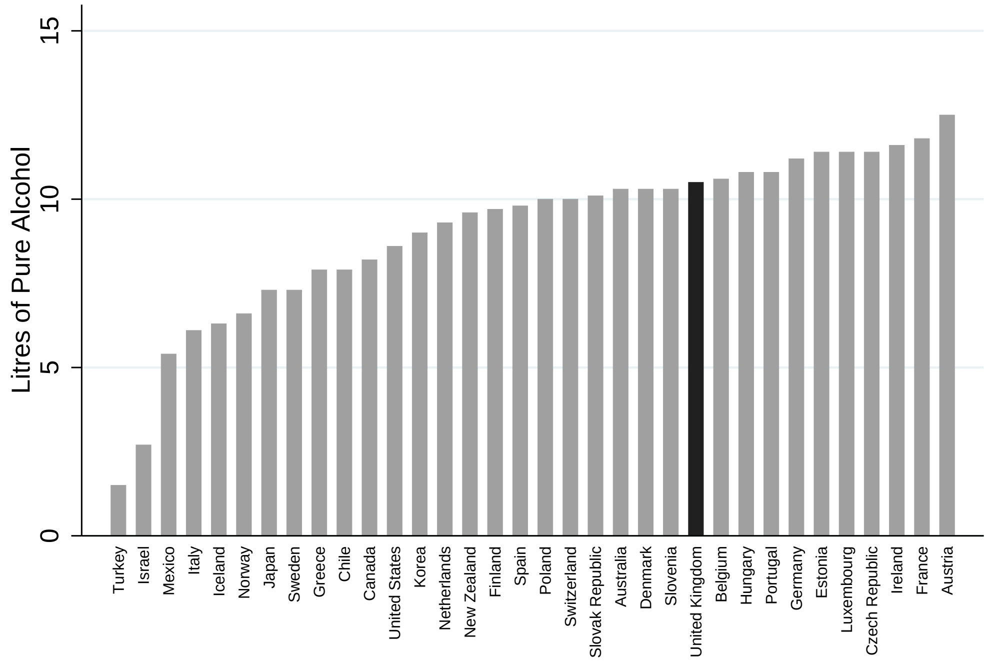
1.1 General Background

1.1.1 Alcohol - An Overview

This thesis is concerned with alcohol - a product which has been in existence for thousands of years and is consumed by a large number of people worldwide. Its place in society appears to be accepted in most countries, with very few countries having an outright ban on the sale of alcohol. Figure 1.1 shows the distribution of mean alcohol consumption per adult (aged 15+) by country within the OECD. The United Kingdom is shaded darker to highlight its position towards the upper end, with consumption above 10 litres of alcohol per capita per year in 2010 which is equivalent to over 19 units of alcohol per week. This is enough for every adult to exceed the recommended previous weekly limits[1] - 14 units for women and 21 units for men[2]. Furthermore, alcohol consumption in the United Kingdom has increased relative to other comparable countries within the OECD, as shown in Figure 1.2. Of course, both of these figures are in broad-brush in that they reflect only mean per-capita consumption, and mask a whole host of trends in the distribution of alcohol consumption. For example, the decreases

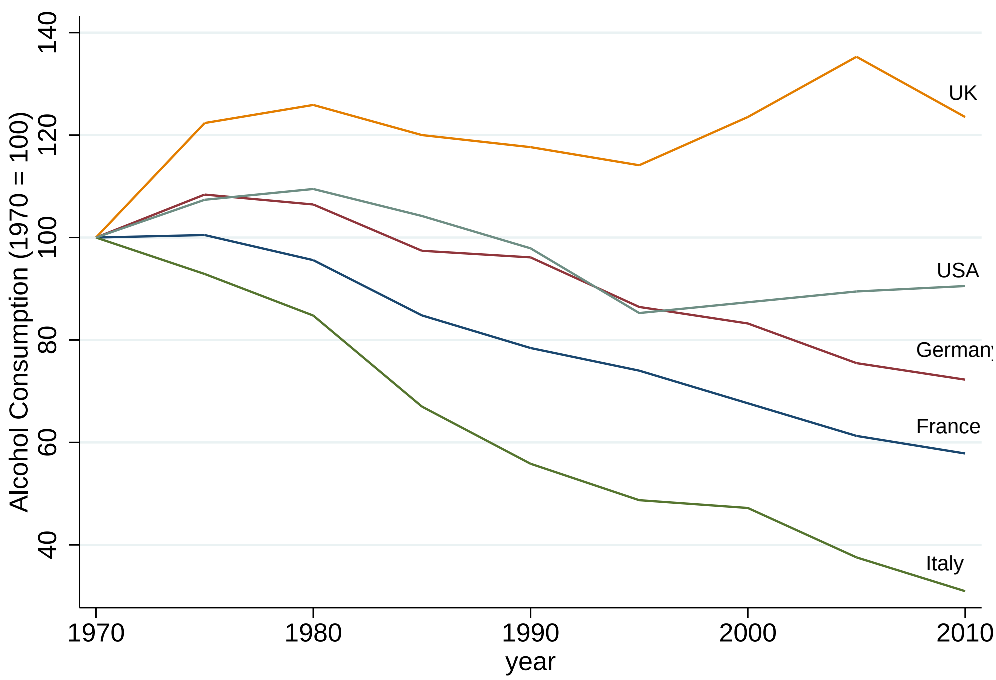
[1] The alcohol consumption guidelines were changed in January 2016 to 14 units for both men and women.
[2] A unit of alcohol is 10ml (8g) of pure ethanol.

Figure 1.1: Mean Alcohol Consumption within OECD



Source: OECD (2015)

Figure 1.2: Alcohol Consumption over Time: A Comparison

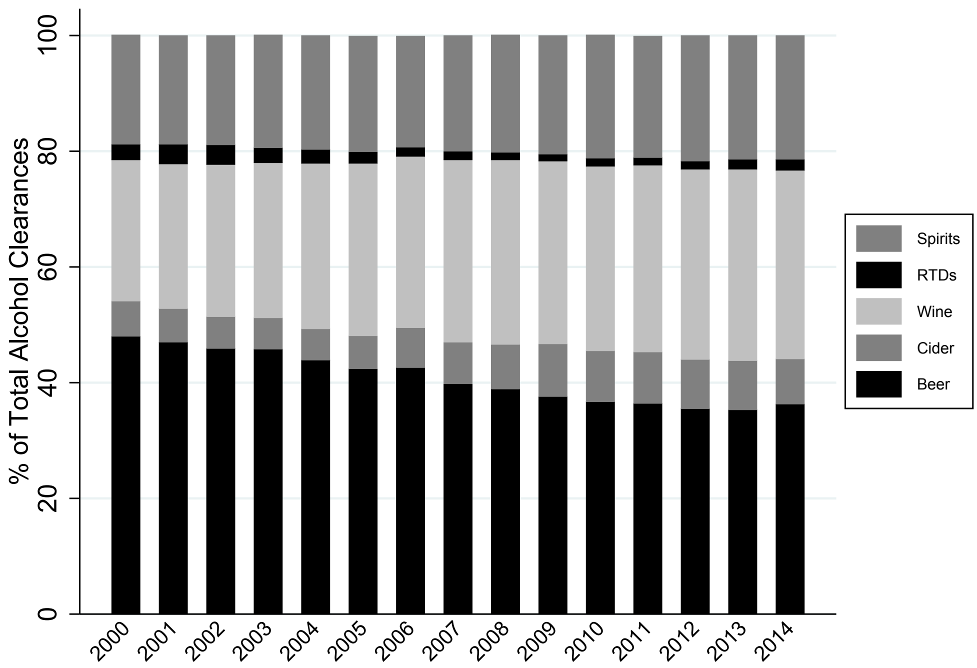


Source: OECD (2015)

in alcohol consumption may be due to population-wide decreases or from certain subgroups decreasing their consumption. It may be that increasing abstention is masking a substantial increase in alcohol consumption amongst some subgroups of the population. It may also be interesting to policymakers *why* alcohol consumption patterns change - is it to do with prices and policy, or just natural shifts in preferences? If pricing and policy is driving any change, then it is important to know exactly how this is working and whose alcohol consumption it is affecting. It could also be that changing demographics are behind the differences in trends across countries.

Figure 1.3 shows the share of total alcohol clearances by drink type. The share of

Figure 1.3: Alcohol Consumption over Time: Breakdown by Drink Type



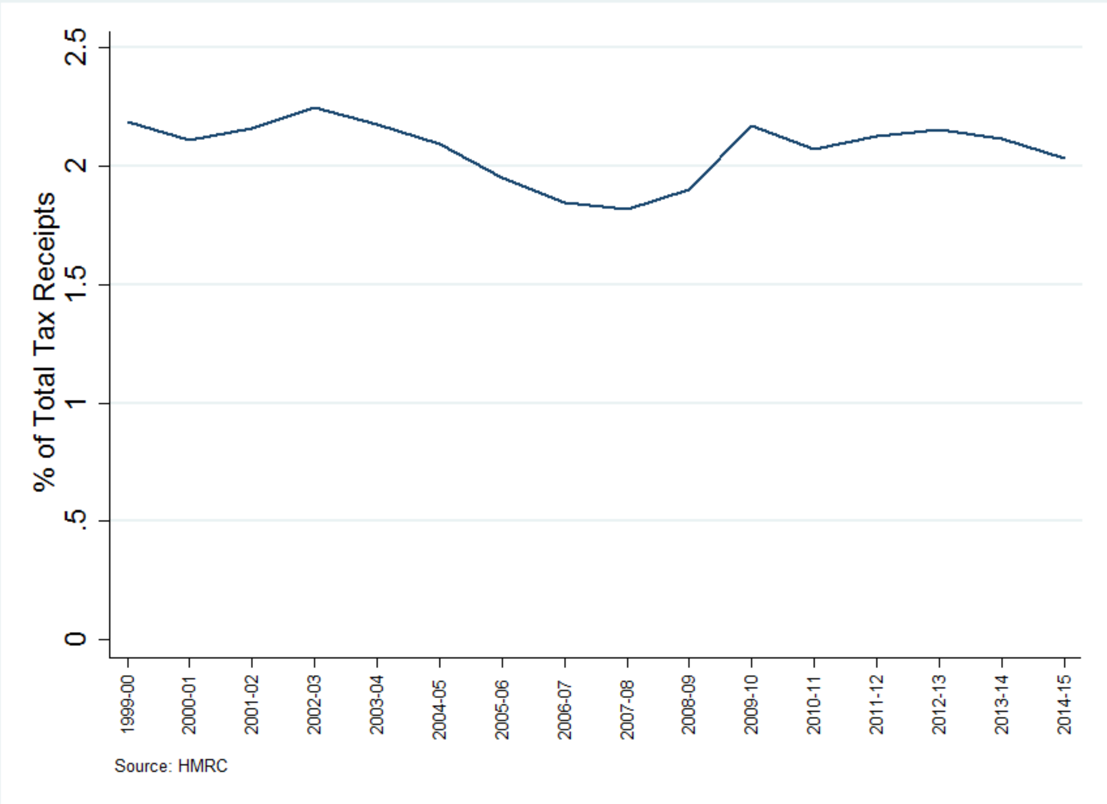
Source: BBPA Handbook, 2015

consumption has fallen over time for beer, from 48% in 2000 to 36% in 2014. Wine consumption has increased as a share of total consumption from 24% to 33%. RTDs, or alcopops, peaked at 3.4% of alcohol consumption in 2002, but their share of consumption has declined since to below 2%.

1.1.2 Why Drinking Matters

Alcohol consumption matters to policymakers for four key reasons. Firstly, it is a substantial source of tax revenue. The average price of a pint of beer in the United Kingdom in 2014 was £2.20, and the corresponding tax was £0.99 - nearly 50% (BBPA, 2015). Alcohol duty raised over £10 billion in the United Kingdom in 2015, roughly 2% of total tax revenue. Figure 1.4 shows that alcohol is a relatively stable source of government revenue. (HMRC, 2015).

Figure 1.4: Alcohol Duty as a Percentage of Total Tax Revenue



Secondly, there is a link between alcohol consumption and health. Alcohol consumption has been linked to cancer (Bagnardi et al, 2000), stroke (Reynolds et al, 2003), liver cirrhosis (Rehm et al, 2010), hypertension (Xin et al, 2001) and injury (Taylor et al, 2010). However, there is a potential J-shaped relationship between alcohol consumption and heart disease, whereby low consumption shows a reduction in the risk of coronary heart disease but high consumption increases the risk relative to non-drinkers (Corrao et al, 2000; Roerecke and Rehm, 2014). This relationship has been questioned (Chikritzhs et al, 2009) because it does not distinguish between previous heavy drinkers who have stopped drinking ('sick quitters') and lifelong abstainers. Reliable, causal estimates of the relationship between alcohol and health harms are hard to produce because of the simultaneous relationship between health and alcohol consumption. Heavy alcohol consumption during pregnancy is linked with adverse child outcomes including low birthweight (Nykjaer et al, 2014). For this reason, the UK Department of Health recommend that pregnant women do not consume alcohol [3].

Thirdly, alcohol consumption is linked to several other, non-health-related costs. Driving under the influence of alcohol increases the risk of causing an accident - "drivers with alcohol in their blood are seven times more likely to cause a fatal crash" (Levitt and Porter, 2001). Alcohol is also related to violence - Boden et al (2012) find that those with five or more alcohol abuse or dependence (AAD) symptoms were more than twice as likely to commit violent acts, including intimate partner violence. Alcohol consumption is also related to workplace absenteeism and lost productivity (Bouchery et al, 2011) and crime (Ensor and Godfrey, 1993; Popovici et al, 2012). Whilst there is a relationship between alcohol consumption and risky sexual behaviour (Agius et al, 2013), there is no evidence that the relationship is causal. Since alcohol is a 'risky' product, in that it increases the risk of certain health conditions, it may be used more frequently by risk-seeking individuals who engage in other risky behaviours such as risky sexual behaviour as well as smoking and gambling. The Institute for Alcohol Studies estimate that alcohol costs society £21 billion, with £3.5 billion on health costs, crime costing £11 billion and lost productivity costing £7 billion.

Finally, alcohol is a potentially addictive substance. In the 2007 Adult Pyschiatric Mor-

[3] This advice was altered in 2016; the previous recommendation was no more than 2 units (roughly equivalent to a glass of wine) per week. This compares to a recommended limit of fourteen units per week for non-pregnant women.

bidity Survey, over 8% of men were found to display symptoms of alcohol dependence as indicated by a Severity of Alcohol Dependence Questionnaire (SADQ) score of four or more (McManus et al, 2009). In the 2012-13 financial year, over 100,000 people received treatment for alcohol dependence (PHE, 2013). There is evidence that heavy alcohol consumption may be consistent with Becker and Murphy's (1988) theory of rational addiction (Bentzen et al, 1999; Baltagi and Griffin, 2002). The theory of rational addiction assumes that individuals make consumption decisions regarding potentially addictive substances in the full knowledge that current consumption means higher future consumption is required. Whether addiction is rational, and more generally the behaviour of addicts, will be of interest to policymakers who need to know how best to reduce the costs associated with addiction.

1.1.3 Alcohol and Externalities

The previous subsection detailed several negative consequences of drinking. However, a large burden of these consequences rests on the individual. The theory of rational addiction would suggest that individuals internalise some of the costs - including the health effects that alcohol consumption carries. Of course, policymakers may argue that individuals are making ill-informed decisions and thus policy is needed, but there is also a less paternalistic case for policy which is that high consumption of alcohol imposes external costs. These are costs which are not borne by the individual, and so any individual maximising their own welfare would not take them into consideration. Although poor health is mostly a cost borne by the individual in terms of loss of quality of life, poor health requires more healthcare which is publicly funded. Scarborough et al (2011) estimate that alcohol costs the National Health Service £3.3 billion. These costs are calculated by weighting healthcare costs by their alcohol-attributable fraction (AAF) such that if 50% of neck cancer is estimated to be caused by alcohol, and treating cancer costs the NHS £X, then the alcohol-related cost of cancer is simply X/2. Of course, these costs rest crucially on the alcohol-attributable fraction, which is difficult to causally estimate. Non-health externalities include injury from collisions caused by a drunk driver, the cost to the victims of alcohol-related crime and anti-social behaviour. Greenfield et al (2009) found that 60% of people in the United States reported being the subject of externalities surrounding alcohol consumption over their lifetime. The externalities included assaults and financial problems. Almost 1 in 10 respondents reported being the subject of externalities in the past year. Gell et al (2015) report that 78.7% of respondents in North West England were harmed by someone else's drinking in the past year. More research is needed into the calculation of the external costs of alcohol, but this is outside of the scope of this thesis.

There are several ways to deal with externalities to reduce the associated welfare loss. A popular method of addressing externalities is through the use of Pigouvian taxes, a subject which was addressed by Bhattacharya (2016). However, it is generally thought that the marginal external cost of alcohol is increasing, such that heavier drinkers impose greater external costs (as well as greater private costs on themselves). A Pigouvian tax would therefore need to increase with consumption, which is not feasible in the context of alcohol.

1.1.4 Alcohol Policy

There are several policy options available to policymakers wishing to reduce alcohol consumption. A handful of countries have an outright ban on alcohol, and the United States imposed prohibition on the sale of alcohol during the 1920s. A more common policy is the restriction of the sale of alcohol to young people, although the age limits vary by country. This is motivated by the argument that young people are not able to make fully informed decisions. The sale of alcohol is also restricted in many countries through licensing systems, which vary by jurisdiction. For example, in Sweden alcoholic beverages stronger than 3.5% in volume can only be sold by the state-owned monopoly Systembolaget. Similar arrangements are in place in Norway (Vinmonopolet), Finland (Alko), Iceland (Vinbuo), the majority of Canadian states, and several states in United States. There is no good evidence on the impact of such regulation on alcohol consumption, since there has been little variation in the structure of the regulation. Although in British Columbia the market was semi-privatised, and alcohol sales increased (Stockwell et al, 2009), it is not clear that the two are causally related. The increase in outlet density may have been driven by an anticipated increase in alcohol consumption. Gmel et al (2015) found no evidence of causality between outlet density and alcohol consumption. In the United Kingdom, sellers of alcohol must have a licence which is granted by the corresponding Local Authority. Premises may be licensed for the 'on'-trade, where the alcohol is consumed on the premises (such as bars and restaurants), or for the 'off'-trade, where alcohol is consumed away from the premises (such as supermarkets). Licence holders are required to sell alcohol responsibly - enforcing age restrictions, keeping order (such as through security staff), and are not permitted to sell alcohol to drunk people.

Age restrictions on the sale of alcohol vary by country. For example, in the United States the minimum legal age to purchase alcohol is 21 whilst in Germany it is 16 for beer and wine. Because there has been little change in the minimum legal drinking ages it is hard to get any reliable evidence on their effect. In 1982, the USA standardised the minimum purchase age to 21. Prior to this, the minimum purchase age was set at state-level. There is an extensive amount of research on the effect of this change (Saffer and Grossman, 1987; Cook and Tauchen, 1984; DuMouchel et al, 1987; Males, 1987; Decker et al, 1988), although it is mostly focused on drink-driving amongst youths. There is some evidence that it had little effect on heavy drinking amongst the student population (Engs and Hanson, 1988). A more recent example of a change is New Zealand, which lowered the minimum purchasing age from 20 to 18 in 1999. This was found to increase the risk of traffic collisions amongst young people (Kypri et al, 2006) but this might be expected. Although the initial age of drinking is correlated with later alcohol use, in that those who started younger tended to drink more heavily (Pitkänen et al, 2005), there is no reason to believe this to be causal.

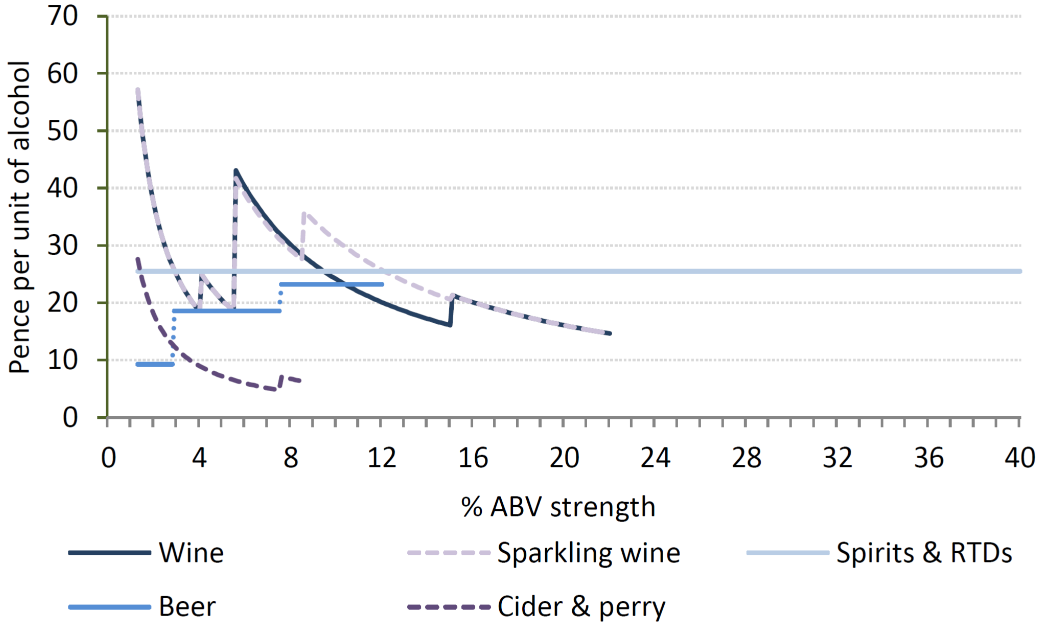
The sale of alcohol can also be restricted to certain times. In the United Kingdom, the Licensing Act 2003 introduced more flexible opening hours. Although there was concern that this would lead to greater social costs (Foster, 2003), it was found to have no impact on crime and disorder (Hough and Hunter, 2008). It was also found that liberalising opening times through the Licensing Act 2003 reduced traffic accidents, especially amongst young drivers (Green et al, 2014).

1.1.5 Alcohol, Prices and Taxation

This thesis, however, is primarily concerned with the most commonly used policy lever in reducing alcohol consumption: price. The government can affect prices through differing methods of taxation - beer duty is the oldest source of revenue still collected by the UK government - as well as other price-based mechanisms such as setting minimum prices. Although national governments are free to set their own tax rates, European Union harmonisation meant that the structure of taxes is the same across the European Union. For example, some drinks are directly taxed on their alcohol content (spirits, and to some extent beer) whilst others are taxed simply per hectolitre of finished product (such as most wine). Figure 1.5, taken from the Institute for Fiscal Studies (IFS, 2011) shows how duty rates differ per unit of alcohol (where a unit of alcohol is equal to 10ml of pure alcohol). Figure 1.6, Figure 1.7 and Figure 1.8 show the effective duty per hectolitre of beverage for beer, wine and spirits respectively within the European Union. Again, the UK is highlighted to show that it is near the top for every single drink type. It is worth noting that the majority of countries do not impose duty on wine, especially those who produce wine. In addition to this, the UK government introduced a 'duty escalator' in 2008, which compelled the government to increase duty on alcohol above inflation every year. The duty escalator was scrapped in 2014.

The impact of price on alcohol consumption has been widely researched, although there

Figure 1.5: UK Duty Rates by Drink Type and Strength



are gaps in the literature which this thesis will address in due course. Overall, it seems that price increases are effective at reducing total consumption (Gallet, 2007; Wagenaar et al, 2009), although its effect on the distribution of drinkers is unclear, as is the effect on drinking behaviour. More information is needed on the distributional effect, both in terms of the effect on heavy versus light drinkers and also the effect on different subgroups of the population. Addicts are unlikely by definition to be particularly responsive to price, since it is costly to reduce consumption. However, rational addicts may be sensitive to anticipated future price increases since they know that future consumption is affected by current consumption. Furthermore, raising prices may discourage potential future addicts from becoming addicted. The role of price on whether a person even drinks in the first place also merits further examination.

Because taxes may not be fully passed through (Ally et al, 2014), some governments have considered the use of floor prices which restrict the price of alcohol at the bottom of the market. Floor prices are necessary if incidence is a worry, since drinks manufacturers can absorb some of the tax increase rather than raise prices. Although this

Figure 1.6: Duty per Hectolitre of Beer

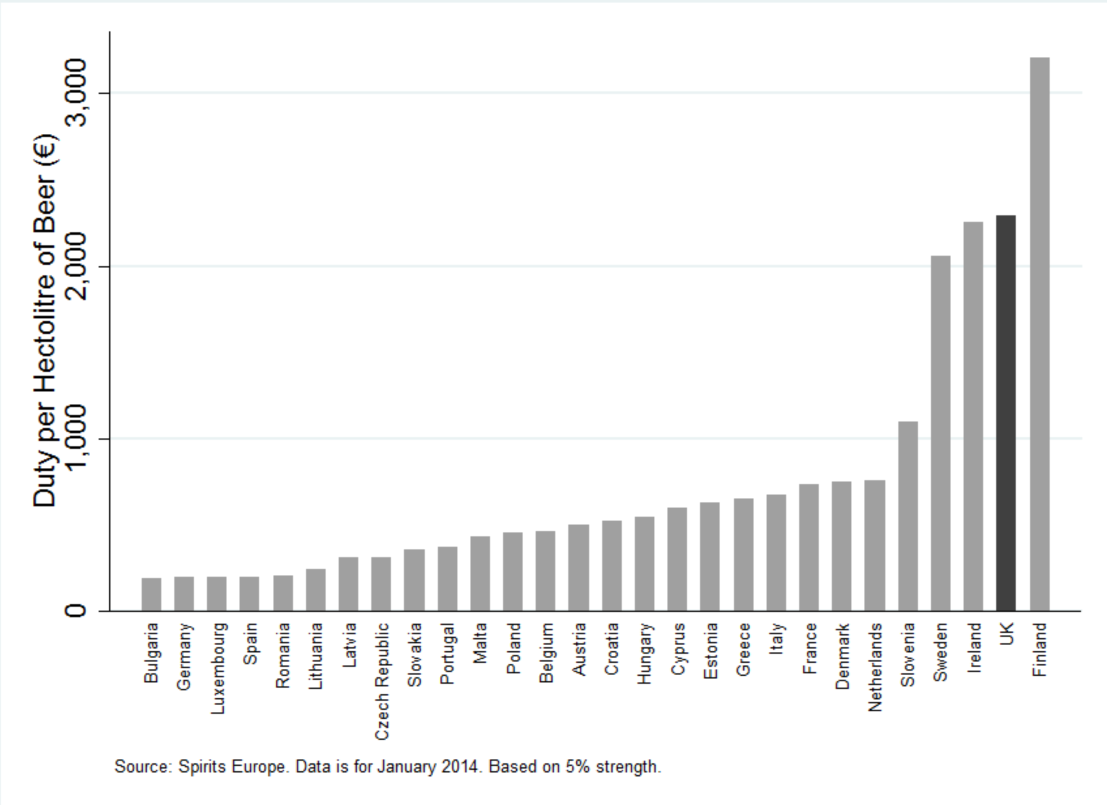


Figure 1.7: Duty per Hectolitre of Wine

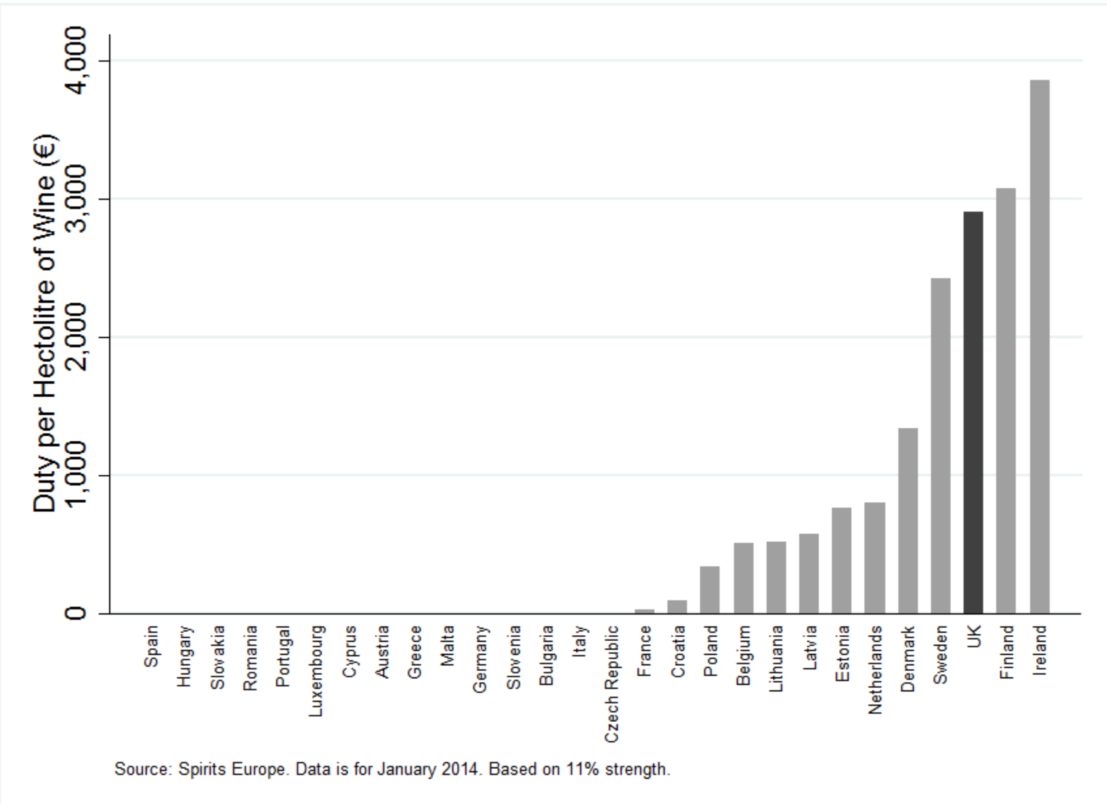
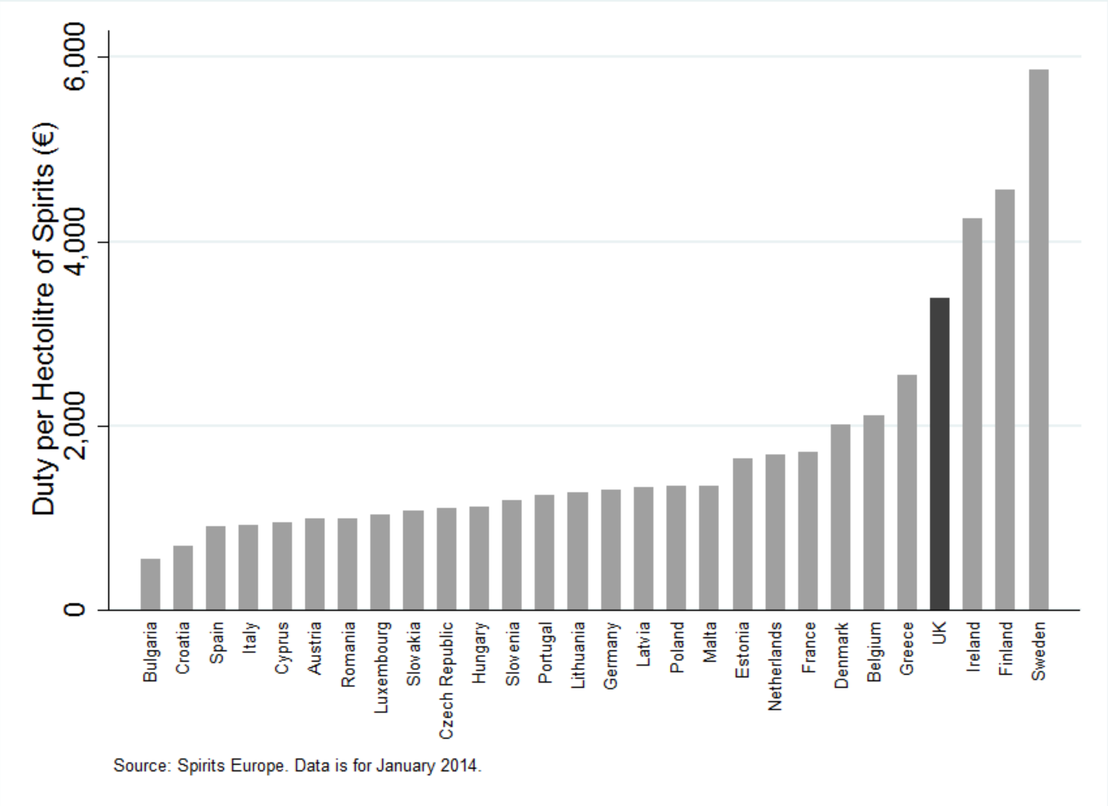


Figure 1.8: Duty per Hectolitre of Spirits



is not important from a tax revenue perspective, it is important to health policymakers who would see a reduced effect from tax increases. However, the research on minimum pricing is limited since it is only used in a few jurisdictions including some Canadian provinces. Stockwell et al (2012) found that raising the minimum price of a beverage by 10% reduced consumption of that beverage relative to others by 16%, and that alcohol consumption fell by 3.4% for a 10% increase in the minimum price. Since minimum prices vary by state, it is a weakness that the study did not use another state as a control case and implement difference-in-difference analysis, and instead simply looks at how alcohol consumption changed relative to how the minimum price changed. There is also no examination of who was affected by minimum pricing, or how minimum price changes affect the drinking *distribution*. This is surprising, since minimum pricing is specifically cited as a good mechanism at targeting the heaviest drinkers, who tend to purchase the cheapest alcohol (Ludbrook, 2009; Black et al, 2011). In the United Kingdom, the evidence on minimum pricing is based on hypothetical models (Purshouse et al, 2010; Holmes et al, 2014; Brennan et al, 2014a; Brennan et al, 2014b), and are sensitive to the model inputs, one of which is the price elasticity of demand for various alcoholic beverages.

Another important consideration for policymakers is that the majority of drinkers drink in moderation, and any price increases will have an effect on the consumer surplus enjoyed by these moderate drinkers. It is only the harmful drinkers who are imposing significant external costs on society. Cook (2008) claimed that, if tax revenues were redistributed across the population, taxing alcohol provides a "free lunch". However, this is only true from a utilitarian perspective, since the heavy drinkers would pay more and abstainers would gain more than light drinkers. Furthermore, estimating consumer surplus requires knowledge of the shape of the demand curve, the price elasticity of demand, and the income elasticity of demand.

1.2 Motivation and Aims

With all this in mind, this thesis aims to extend the literature in three crucial areas. Firstly, it examines the distributional effect of alcohol price changes. This is vital information for policymakers because it will better inform the expected effects of policies such as minimum price which affect heavy drinkers more than light drinkers. The current modelling for the United Kingdom makes restrictive, and possibly unrealistic, assumptions about how different drinkers respond to price changes. Secondly this thesis looks at how, and even whether, price affects non-purchase of alcohol. There are three distinct reasons why non-purchasing is observed in data, each with specific consequences for analysis. Lastly, this thesis looks at how the drinking distribution has changed across different birth cohorts and over age, including the role of price on alcohol consumption across birth cohorts. This thesis is a valuable contribution to the existing literature.

1.3 Structure and Content

This thesis is presented as three distinct empirical research chapters, although there are overlapping elements. As well as chapter-specific conclusions, the thesis finishes with a general discussion of the work presented.

1.3.1 Brief Overview of Chapter 2

Chapter 2 uses both conditional and unconditional quantile regression to estimate the differing response to price across the drinking distribution. The advantage of unconditional quantile regression is that we are interested in heavy drinkers rather than heavy *conditional* drinkers. Whilst addiction might predict that heavy drinkers are less responsive to price changes, the current modelling for the United Kingdom either uses constant price elasticities or models heavier drinkers as being more responsive to price changes. Chapter 2 also examines how different drinkers respond to price changes by changing the *quality* of their beverages, using the price paid per unit of alcohol as an indicator of quality. It also extends the literature by looking at how the use of an endogenous 'price' variable, which encapsulates quality as well as true price differences, can bias any elasticity estimates. This is not a trivial point - many studies make use of expenditure data to calculate 'price' variables in this manner. Using unit values introduces price endogeneity if there is a relationship between the amount one drinks and the price (and quality) of the drink. The analysis finds that heavier drinkers respond to price by adjusting quality more than quantity, whilst the reverse is true for lighter drinkers, suggesting that the large price increases needed to reduce heavy drinkers' consumption may lead to large losses of consumer surplus for the majority of drinkers.

1.3.2 Brief Overview of Chapter 3

Chapter 3 uses the same expenditure diary data to analyse in more depth the three causes of non-purchasing - infrequent purchase, price-related abstention, and non-price-related abstention. Assumptions about why non-purchase occurs will carry different biases on any estimated price elasticities since price works differently in each cause. If every non-purchasing household is abstaining for non-price-related reasons, then studies using a sample of purchasing households are unbiased. However, if abstention is caused by price, whereby households would purchase alcohol if it was cheaper, then studies using only the purchasing sample will be biased because they are not taking this response into account. This study models the demand for alcohol using a variety of different techniques, building up to a double-hurdle model. Because the double-hurdle model ideally requires a variable to feature in one hurdle but not the other for identification, a novel exclusion restriction predicting abstention is used. It is found that the price elasticity of demand for alcohol is fairly consistent across model specification, but that the Tobit model tends to produce a larger price elasticity estimate.

1.3.3 Brief Overview of Chapter 4

Chapter 4 uses a long-running UK cross-sectional household survey to create synthetic cohorts. It is well understood from a single cross-section that alcohol consumption decreases with age, but the change in consumption across different birth cohorts is more interesting to policymakers. Instead of collapsing consumption to the mean as is done in the majority of the literature, chapter 4 examines the change in the distribution of drinking across cohorts. It also looks at whether price plays a role in determining differences across birth cohorts' alcohol consumption, since it might be expected that higher prices deter younger generations from drinking.

Chapter 2

Quality or Quantity? The Differing Response to Price Changes across the Drinking Distribution

2.1 Introduction

The majority of the literature estimates the elasticity of demand at the mean of the drinking distribution using either aggregated time series data (eg. Levy and Sheflin, 1985; Eakins and Gallagher, 2003) or some extension of ordinary least squares (eg. Huang, 2003; Collis et al, 2010; Meng et al, 2014a). This is useful to know for aggregate reasons, for example if a policymaker wants to know how much a tax increase will affect consumption and future tax receipts. However, the policymaker may want to know the effects of a price change on individual consumption, perhaps for health reasons. As set out in the introduction to this thesis, it is thought that the marginal cost of alcohol is non-linear. This means that the tenth unit (for example) is more harmful to health, and more costly to society, than the first. This is reflected in the Canadian and Australian drinking guidelines, which are based on the level of consumption where harms are the same as abstention[1]. It may well be the case that heavy drinkers respond differently to price changes than do moderate drinkers, and if this is the case then the health gains from a

[1] An interesting observation is that these guidelines differ even though they are based on the same concept. Australian men are advised not to exceed 140 grams of alcohol (roughly 18 UK units) a week, whilst Canadian men are advised not to exceed 190 grams (roughly 24 UK units) a week.

price increase depend crucially not only on how much average consumption falls, but where in the distribution these falls occur. The effect of minimum unit pricing, which explicitly targets the heaviest drinkers since they generally buy the cheapest alcohol (Ludbrook, 2009), will depend on the price elasticity of demand by different drinkers, as well as their ability to switch to even cheaper alternatives. It may be the case that, after minimum pricing, heavy drinkers substitute some of their more expensive alcohol to cheaper alternatives.

It is likely that heavy drinkers respond differently to price changes. Firstly, the heaviest drinkers may be addicted and consume alcohol at any price. The cost of reducing consumption may increase with consumption because heavy drinkers have built up a tolerance to alcohol, so that a reduction of a unit for a heavy drinker is more difficult than for a light drinker. The non-addicted heavy drinkers may still have a drinking habit that persists despite price increases. However it is also possible that the lightest drinkers, for whom alcohol expenditure represents such a small proportion of total expenditure, are affected less by price changes than heavy drinkers.

Similarly, three different stories are possible with the quality response to price across the distribution. Firstly, there may be no noticeable difference across the distribution. Secondly, heavy drinkers have the biggest incentive to seek out the lowest prices. If search costs are fixed, for example taking a bus to an out-of-town supermarket where prices are lower, then the heavy drinkers have more to gain from search. This is similar to the framework used by Varian's (1980) theory of sales, which used 'informed' and 'uninformed' customers. If we suppose there to be a fixed cost of becoming 'informed' then it only makes sense for heavier drinkers to find it worthwhile to become 'informed' since they have the most to gain. Finally it is possible that, since heavy drinkers seek out the cheapest alcohol, they are worst placed to adapt to higher prices by seeking out lower quality products because there is a lower bound to quality. There is also the potential for heavy drinkers to not be addicted, but instead have a high discount rate. This means that they value the immediate pleasure of drinking over the distant health effects of their heavy drinking. If this is the case, then these myopic heavy drinkers will be less likely to take the trouble of searching for a lower price.

This work uses quantile regression techniques to examine firstly whether heavy drinkers respond differently to price changes than moderate drinkers, and secondly how price changes, such as tax increases, affect the distribution of prices paid. The work is done using repeated cross-sectional expenditure data collected over eleven years to give a large representative sample. This chapter begins with an overview of the literature, firstly the relationship between price and quantity and secondly the relationship between price and quality. It then discusses the data and methods used, before presenting and discussing the results. The results show that the price elasticity of demand for alcohol is less elastic for heavier drinkers, with a price elasticity of -0.23 for the upper decile of drinkers compared to -0.89 for the lowest drinking decile, both significantly different to the mean price elasticity calculated. The relationship between price and quality shows that heavier drinkers absorb price increases relatively more than lighter drinkers by substituting towards lower quality alcoholic drinks. The price elasticity of quality demanded is -0.28 for the lower quartile of the drinking distribution, compared to -0.58 for the top quartile.

This chapter is an important contribution to the literature. It is vital for policymakers to know how price affects the drinking distribution because of the non-linear relationship between consumption and harms. This chapter is the first work to assess simultaneously how price changes affect quantity and quality of alcohol consumed. It is also the first work to use unconditional quantile regression when estimating the elasticity of demand for alcohol. In doing so, it also compares results generated from conditional quantile regression with the newer method of unconditional quantile regression. From a policy perspective, it is unconditional quantiles which matter, since it is heavy drinkers who impose the greatest costs rather than people who are heavier drinkers than expected.

2.2 Literature Review

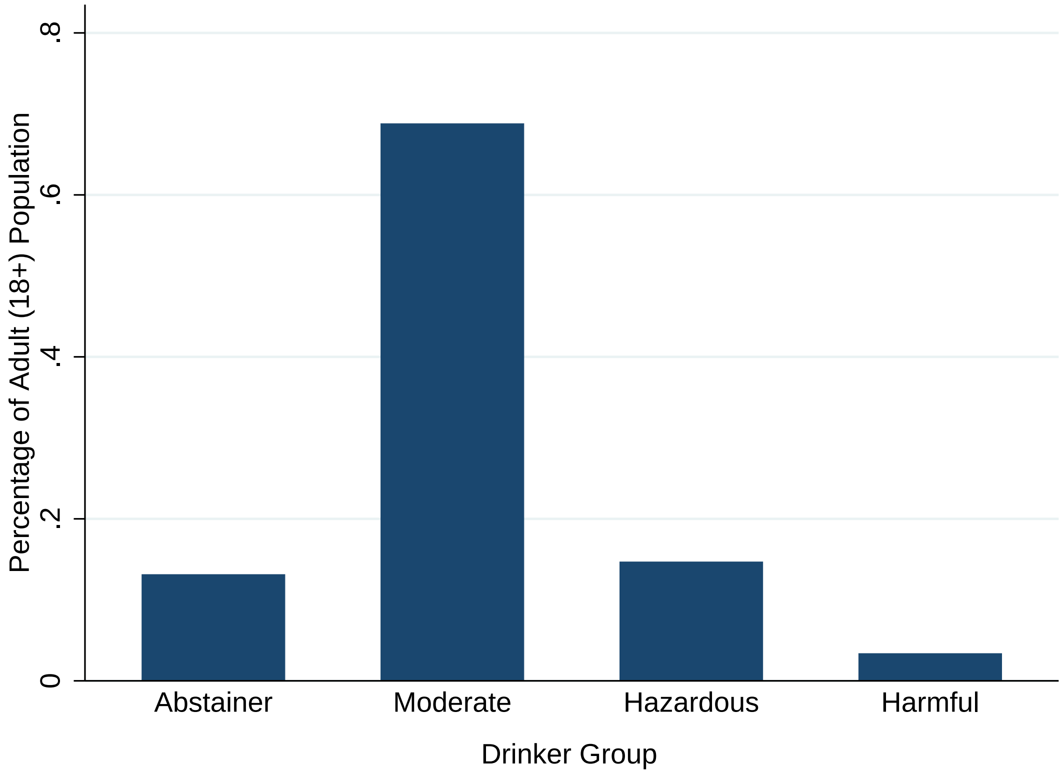
2.2.1 Quantity Response across the Drinking Distribution

Manning et al (1995) was the seminal application of quantile regression in the context of estimating the price elasticity of demand for alcohol. Quantile regression minimises weighted least absolute deviations, rather than squared deviations as in OLS. The weight depends on the quantile, such that positive and negative deviations are equally weighted in a median regression. The authors use a single cross section of data and a (log) price index which is based on the weighted average of three drinks (one beer, one whisky, and one wine) using average population level shares. The variation in the price is effectively driven by geographical differences, so the estimated elasticity parameters may be reflecting geographical differences in tastes and incomes. If areas with a taste for alcohol face higher prices, it would be expected that the elasticities would be biased towards zero. There may also be measurement error in this price and this will imply attenuation - not necessarily the same across all quantiles. This is an important point because the price variation may differ across the price distribution, meaning that price variation is overstated for some parts of the drinking distribution. The authors allow for interactions between price and income and non-linearities in price, and provide estimates of the probability of drinking (using a logit), conditional drinking levels, as well as double-log quantile regression estimates conditional on drinking. The results from Manning et al (1995) suggest a U-shaped relationship between consumption level and price elasticity, with the middle of the drinking distribution being most responsive to price changes relative to the tails of the distribution. They also find that the elasticity estimate for the heaviest drinkers is not significantly different to zero. This is an important result because it is likely that these heavy drinkers are causing the greatest harms yet price may not be an appropriate tool in reducing their consumption. Furthermore, it is possible that the three drinks used to define prices are not purchased by heavy drinkers. Unless the distribution of alcohol prices changes in line with price changes for these specific drinks, the price index is not reflective of changes in price for all alcohol. There is no reason to think that a price increase in Heineken lager must occur at the same time as a price increase in Guinness, or Bollinger champagne. As mentioned later in this chapter, tax pass-through rates may vary across the price distribution and thus even tax changes may have different effects on different drinks.

Saffer et al (2012) use both quantile regression and finite mixture models to examine the role of price and advertising on consumption across the drinking distribution. Finite mixture models assign individuals into sub-groups based on specific characteristics, with each group having its own model of behaviour, and allow the data to determine the probability of each observation belonging to each sub-group as well as the parameters of each model. The authors use data on US youths from the National Longitudinal Survey of Youth 1997 (NLSY97), which is an annual longitudinal survey with a sample comprising 8,984 individuals aged between 12 and 16 years old on December 31st 1996. The study uses the data from 2002 to 2009, meaning that the youngest panel member is 17 and the oldest panel member is 29. Since the minimum legal drinking age in the United States is 21, whether the respondent is aged under 21 is included as a dummy variable. It should be noted from the outset that this is a study of only young people and is therefore not necessarily representative of the general population. The study uses the price of Heineken beer as a proxy for price, and price varies by region (about 300 communities aggregated to the state level) and time (quarter), which carries the same caveat as Manning et al (1995) that the price may not be indicative of the prices faced by all drinkers across the distribution. Another independent variable is the amount of alcohol advertising, measured as a derived variable which is the product of the number of hours of television and the hours of alcohol advertising on television in the month. This measure could be endogenous if heavy drinkers watch more television. The dependent variable used by Saffer et al (2012) is a derived variable which estimates the number of drinks per month, calculated as the product of the number of drinking days per month and the usual number of drinks consumed per drinking day. There is likely to be measurement error, and the measurement error in each component could be correlated, although perhaps no more so than other measures. The measurement error may also not be consistent over the consumption distribution, although again this is a feature of most alcohol consumption measures used in the literature. The finite mixture model finds that there are two underlying population subsets - the first comprises 69% of the whole population and consumes an average of 8.08 drinks per month, the second comprises 31% of the population and consumes an average of 27.23 drinks per month. The price elasticity estimate for the first group (moderate drinkers) is -0.49, whilst the price elasticity for the second group is not significantly different from zero, implying that demand in this second, heavier drinking group is perfectly inelastic. However, the model predicts that alcohol advertising plays a more significant role in influencing consumption in the second group, with an elasticity of 0.1 compared to 0.05. The quantile regression model estimates that lighter drinkers are more responsive to price changes than heavier drinkers, with an elasticity estimate at the 30th percentile of -0.506. The price elasticity estimate is not significantly different from zero after the 60th percentile, suggesting that a substantial minority of the population has a perfectly inelastic demand for alcohol.

Purshouse et al (2010) estimate the price elasticity of demand for sixteen drink categories, comprising of four different drink types (beer, wine, spirits, ready-to-drink (RTD)), sold at two different locations (on- and off-premise) and at two different price points ("high" and "low" price). The detailed workings are contained within a separate report by Brennan et al (2009), as well as the supplementary appendix of Purshouse et al (2010) since the article is concerned primarily with estimating the health effects of a minimum unit price. The authors use unit values generated by dividing expenditure on each drink by quantity in alcoholic units. The cut-off for "low" price alcohol is £0.30 per unit for off-trade alcohol and £0.80 per unit for on-trade alcohol. These arbirtrary

Figure 2.1: Drinker Group Distribution from GHS 2006



cut-offs may cause simultaneity bias, because the price of 'low' price goods cannot rise above £0.30 per unit. If products at the margin switch from being 'high' price goods to 'low' price goods, then the demand for low price beverages falls mechanically. The dependent variable is the natural logarithm of units of alcoholic drink for each equation, and the main independent variables are price of each drink type derived by dividing expenditure by quantity. It is unclear how the price is calculated for individuals who do not purchase a product. To model the differential response across the drinking distribution, the authors split the sample into three distinct subgroups - moderate, hazardous and harmful drinkers - based on the number of units consumed. Here, moderate drinkers are men (women) who consume less than 21 (14) units per week, harmful are men (women) who consume more than 50 (35) units, and hazardous are those in between. Figure 2.1 shows the distribution of drinkers from the General Household Survey 2006. The method used by Purshouse et al (2010) is essentially endogenous selection into a subgroup, because it is selection based on the dependent variable, which may bias the elasticities. This is noted by Koenker and Hallock (2001) who state that

> "*We have occasionally encountered the faulty notion that something like quantile regression could be achieved by segmenting the response variable into subsets according to its unconditional distribution and then doing least squares fitting on these subsets. Clearly, this form of 'truncation on the dependent variable' would yield* ***disastrous results*** *in the present example. In general,* ***such strategies are doomed to failure*** *for all the reasons so carefully laid out in Heckman's (1979) work on sample selection*"
>
> (Koenker and Hallock, 2001, p.147, emphasis added)

The effect of selecting on the dependent variable, as done by Purshouse et al (2010), can be shown easily through simulation. This is demonstrated in Appendix B. The study also uses individual-level expenditure data, which may be problematic in multi-person households where there may be a mismatch between expenditure and consumption. The authors find that heavy drinkers have, on average, more elastic demand for alcohol than moderate drinkers. For example, the estimate own-price elasticity for high-price, off-premise beer is -0.42 for moderate drinkers compared to -0.57 for hazardous and harmful drinkers. The authors run a separate model which aggregates across all alcohol - which they refer to as a "high level" model - which finds moderate drinkers have a price elasticity of demand for alcohol of -0.47 compared to -0.21 for hazardous and harmful drinkers.

2.2.2 Quantity Response for Different Goods

Several papers have used quantile regression to examine the differential demand elasticity across the distribution. This is especially true for goods, such as alcohol, which have external costs or benefits. For example, Goel and Ram (2004) use cross-sectional US state-level data to model demand for cigarettes using a basic specification. They calculate a mean price elasticity of demand for cigarettes of -1.3, with some variation across the distribution. However, the study has relatively few observations because it is at the state-level and the only independent variables are prices and incomes. The demand for ice cream is the focus of a study by Gustavsen et al (2008) who find that the demand for ice cream is more price elastic for those households who purchase less ice cream, with the 0.5th quantile having a price elasticity of -2.4 compared to -1.2 for the 0.9th quantile. Gustavsen and Rickertsen (2011) look at the impact of a tax increase on the demand for sugar-sweetened beverages because of the link between consumption and obesity. They find that those who consume more sugar-sweetened beverages are less responsive to price changes, and that the price elasticity for the 90th percentile is not significantly different from zero. The authors do point out that, although the absolute value of the elasticity declines as consumption increases, the absolute decrease in consumption also increases since the distribution of sugar-sweetened beverage consumption has a long tail at the upper end. Finally, Gustavsen and Rickertsen (2006) look at the demand for vegetables. The authors use censored quantile regression since non-purchasers are worthy of special consideration, and it is important to model the effect of price on participation in the vegetable market. Unlike with alcohol, the extreme end of the vegetable consumption distribution is the lower tail, as this is where the majority of health problems are caused[2]. The authors find that the price elasticity from the median of the consumption distribution to the upper end is fairly constant, with the estimated own-price elasticity ranging from -0.42 to -0.36. However, the elasticity estimate for the lower quartile and the lowest decile is not significantly different from zero. This is an important finding, suggesting that price-based policies in this context may not be useful in increasing the consumption of vegetables where it is in need of increasing most.

2.2.3 Quality Literature

Trandel (1991) demonstrates, using the heterogeneous commodity "automobiles", that if quality is positively correlated with price then price elasticities will be biased towards zero. If an individual purchasing 20 units of high quality product responds to a price increase by purchasing 20 units of low quality product, then the price elasticity of demand would appear to be perfectly elastic. However, this is only a local effect since

[2] Although this is not quite the same as alcohol and tobacco, since unhealthy people can consume a large quantity of vegetables.

quality substitution can only occur if a lower quality product is available. The work by Purshouse et al (2010) split drinks in to “high” and “low” price to control for quality. One interesting observation is that the cross-price elasticity estimates between the high and low price beverages are small in magnitude. For example, the authors find that if the price of high price beer increases by 1%, the demand for low price beer increases by 0.003%. This suggests that quality substitution does not occur in the alcohol market. Gruenewald et al (2006) use Swedish alcohol retail data from 1984 to 1994 to examine the impact of a change in the alcohol duty rates on alcohol quantity and quality demanded. In 1992, the Swedish alcohol regulator, Systembolaget, changed the structure of duties such that beverages were taxed based on alcoholic strength rather than as a percentage of pre-tax price. The duty change led to a narrower distribution of prices for wine and spirits, but a wider distribution of prices for beer. The authors define quality by the relative price of the drink, and assign drinks into three categories - high, medium and low quality. This is done for three drink types - beer, wine and spirits - giving nine different types. This is similar to the method used by Purshouse et al (2010). The study uses time series data, with the dependent variable being monthly sales of drink type, giving 120 observations. The price variable is a price index constructed from the unweighted average price for each drink type. The study also controls for mean real income per active earner and the monthly unemployment rate. A double-log model is used, and the elasticities are constrained such that the own-price elasticities are equal across drink types. This constraint was not imposed in Purshouse et al (2010). There are some weaknesses to Gruenewald et al (2006). Firstly, the study uses aggregate data so that patterns of change across different subgroups cannot be observed. Secondly, the lack of a comparator means that the effect may have happened regardless of the policy. Testing using a placebo policy could help to eliminate the possibility of this being the case. Thirdly, the tax restructuring did not just alter prices, it fundamentally changed the market. Whereas before a product was taxed based on its pre-tax price, it was now taxed based on the strength of the product. This means that the relative price for a low strength, high quality product reduced compared to a high strength, low quality product.

This means that not only did the price of quantity (in terms of the average price per litre of drink) change, but so too did the price of quality. It does not answer the question of what happens if the price of all alcohol increased across the quality distribution. Finally, the paper does not look at quality substitution across the drinking distribution. This is a crucial piece of information because it is likely that, if the quantity response to price is heterogeneous, the quality response may also be heterogeneous.

2.3 Data

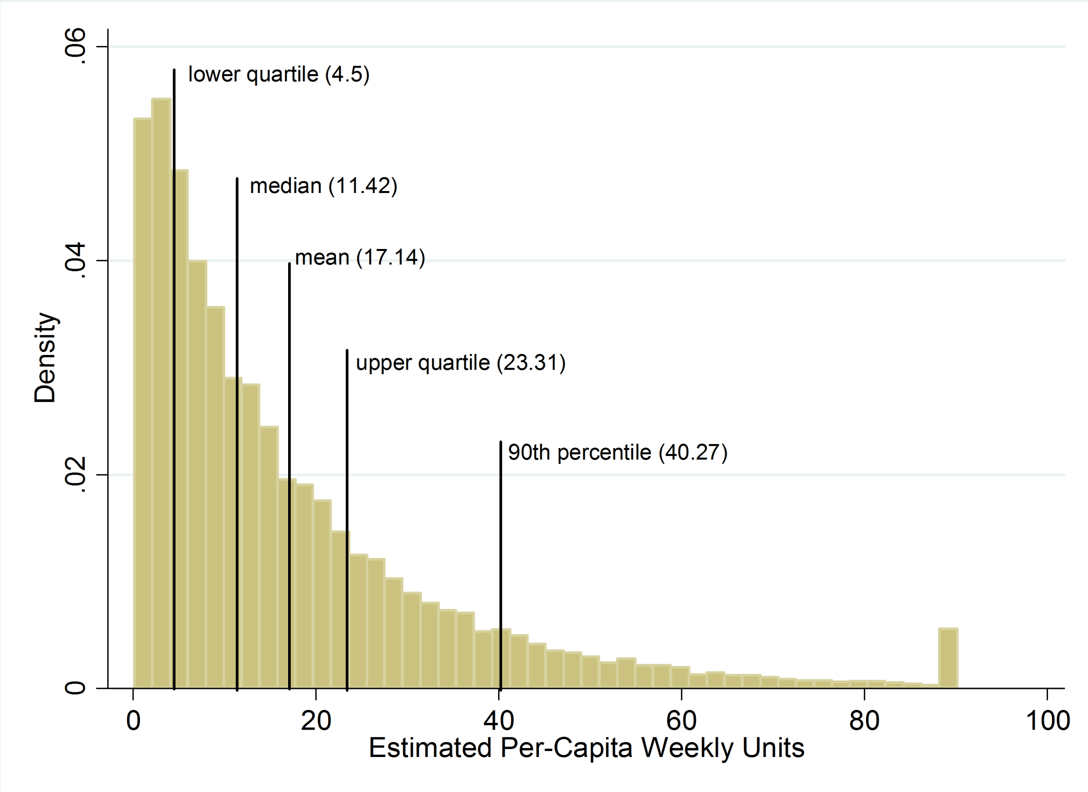
This work uses data from the Living Costs and Food Survey (LCF) from 2008 to 2011, and the Expenditure and Food Survey (EFS) from 2001 to 2007. The surveys are nationally-representative cross-sectional surveys of roughly 6,000 households each year, and comprise of a face-to-face interview and a two week expenditure diary. Because the survey uses private households, some sections of the population are not included such as the homeless, the military, prisoners, and the hospitalised. These population subgroups may drink differently to the private household population, and this is a limitation to the dataset used. The diary data is useful because it includes quantity and expenditure data, which allows unit values to be calculated. Data is again aggregated by household because of the mismatch between purchase and consumption. This is an important distinction from Purshouse et al (2010) who use individual spending records, which may produce biased results. This is especially true in the context of quantile regression, since heavy drinkers may in fact be purchasing for other members of the household. The dependent variable used is the number of units, again calculated using the estimated strengths for each drink type from Purshouse et al (2010). The total number of units is used as the dependent variable because policymakers are likely to care more about the response to a price change by heavy drinkers rather than, say, heavy *beer* drinkers. The analysis is also done separately for aggregate on-premise and off-premise alcohol. Since the LCF/EFS has detailed information on expenditure and quantity (in millilitres), it is possible to calculate a price-per-unit of alcohol by dividing expenditure by the number of alcoholic units. Allowing price to vary by individual is likely to bias the coefficients if heavy drinkers purchase lower price alcohol. For this reason, a price index is formed based on the average price-per-unit in each region and month.

Firstly total expenditure on alcohol is divided by the estimated number of alcoholic units for each household, to generate an average unit price V. This is used to construct an unweighted average of prices within a region and time period, essentially $\overline{V_{irt}}$, to generate the price variable P_{rt}. This variable is then deflated using the retail price index for all items to give the real average price per unit paid in each region and month. Other variables included in the dataset, and used as control variables, are the number of adults in the household, the age of the oldest household member, and the number of children in the household.

2.3.1 Summary Statistics

Figure 2.2 shows the distribution of conditional, per-capita weekly alcohol consumption. This figure is generated by dividing total household units by the number of adults in the household. Of course, a household may comprise one heavy drinker and one light drinker, which Figure 2.2 would treat as two medium drinkers. However, the figure is shown to give an overview of the drinking distribution roughly controlling for household size. The distribution is truncated in the figure at the 99th percentile because of its long tail at the upper end (in one household, per-capita alcohol consumption is 734 units). It is clear that the majority of households are drinking within the guidelines, with a substantial minority exceeding the guidelines. The caveat applies that the distribution is based on alcohol expenditure rather than consumption, meaning that some apparently "heavy drinkers" may in fact be "heavy spenders", and some "light spenders" may not necessarily be "light drinkers" if they consume from stock purchased outside of the two week diary period. For now, this is assumed to be measurement error. Figure 2.3 shows how heavier drinkers pay less on average per unit than lighter drinkers. This may be be-

Figure 2.2: Estimated Per-Capita Weekly Units



cause the heavier drinkers are purchasing the majority of their units in the off-premise whereas the lightest drinking quintile purchase the majority of theirs in the on-premise, as shown in Figure 2.4. Other summary statistics are presented in Table 2.1.

Table 2.1: Summary Statistics

Variable	Mean	Std. Dev.	N
Units	63.094	69.672	47082
Per Capita Weekly Units	17.43	19.433	47082
Real Price per Unit (pence)	72.381	65.563	47082
Real Household Total Expenditure (£)	427.068	316.309	47082
Total Number Adults	1.913	0.735	47082
Number Adult Males	0.942	0.564	47082
Number Adult Females	0.971	0.508	47082
Number of Children	0.586	0.964	47082
Age of Oldest Household Member	51.363	15.636	47082

Figure 2.3: Real Price per Unit Paid by Drinking Quintile

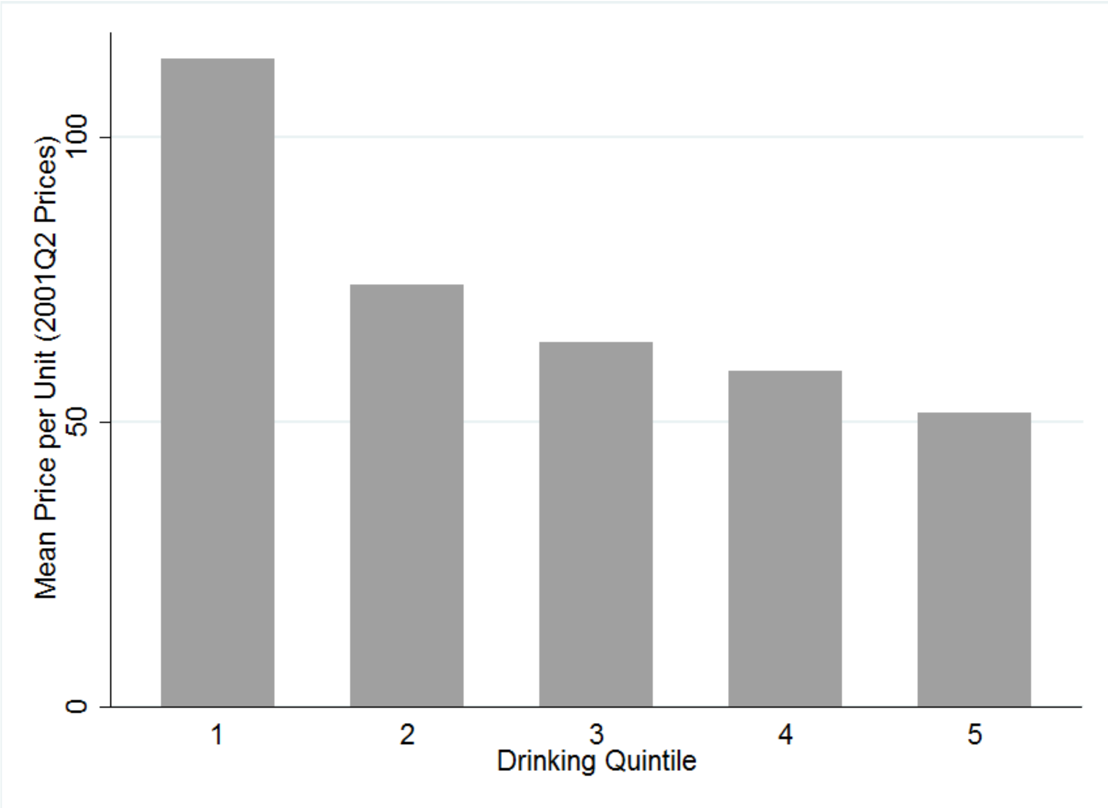
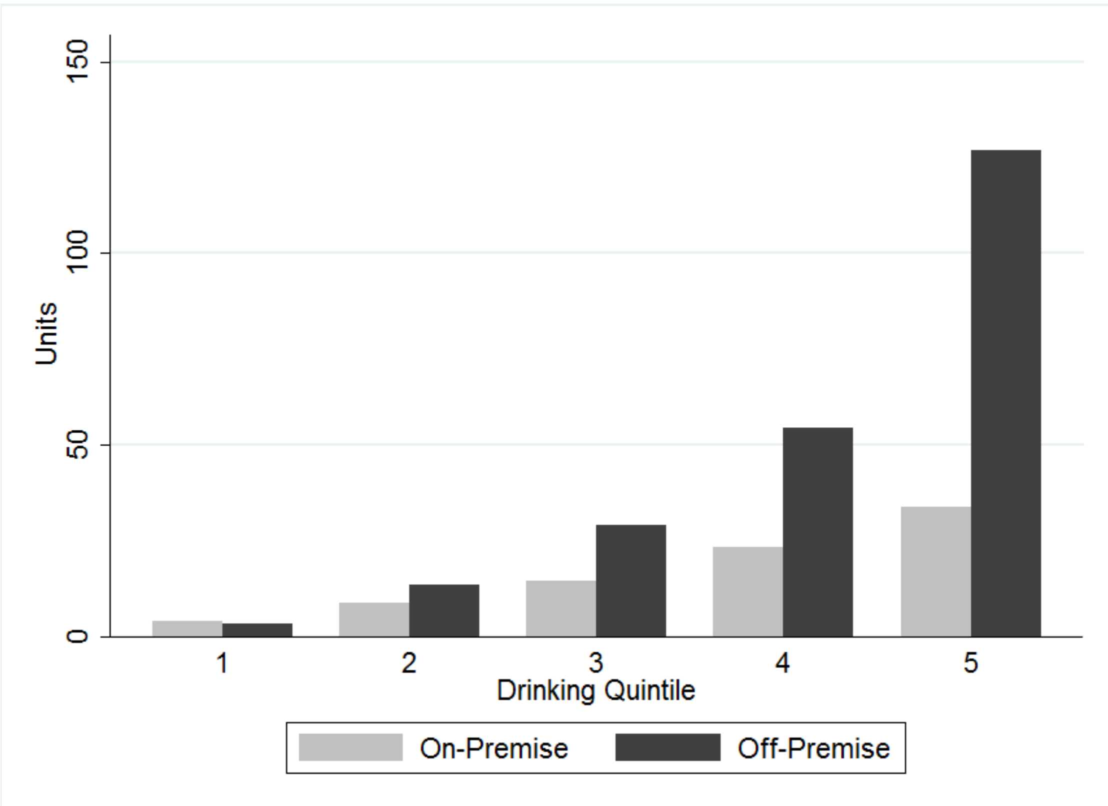
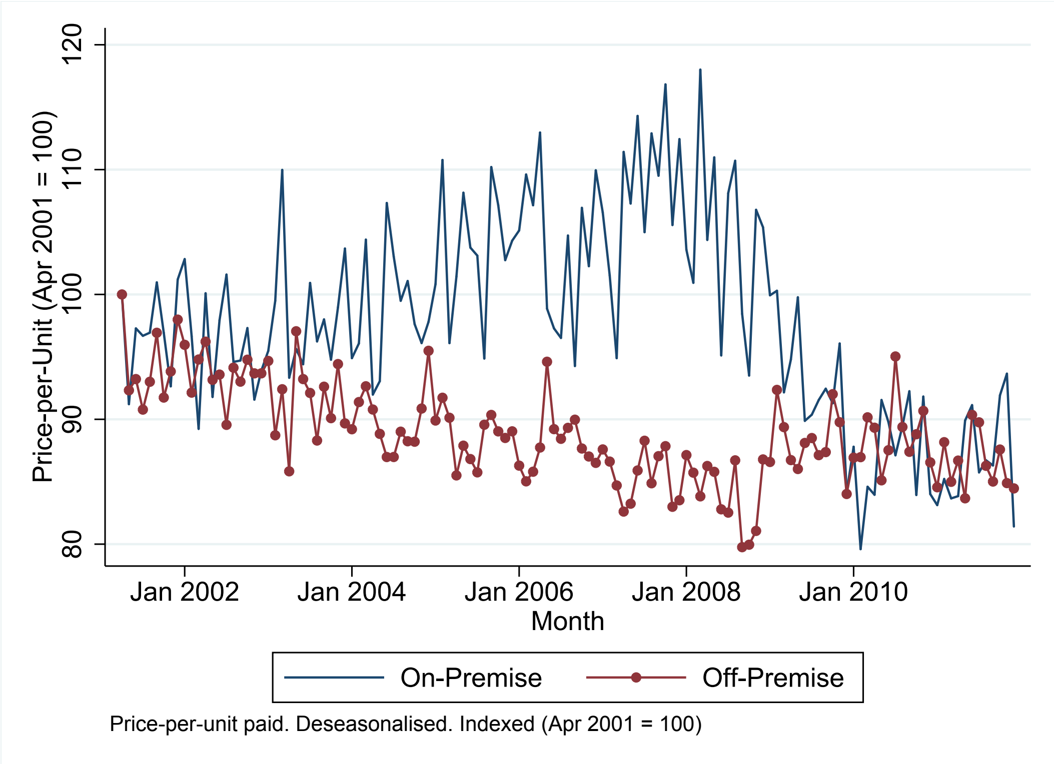


Figure 2.4: On- and Off-Premise Units by Drinking Quintile



Finally, prices over time for on-premise and off-premise alcohol are shown in Figure 2.5. The price of on-premise alcohol has increased over time, compared to off-premise alcohol which has fallen over time. Because the price-per-unit varies by season, the price index has been deseasonalised by regressing price against month and taking the residual.

Figure 2.5: Alcohol Prices over Time



2.4 Methods

2.4.1 Quantity

The first model used is Ordinary Least Squares, as used in the majority of the literature, to estimate the mean elasticity. The model is

$$\ln Q_{irt} = \alpha + \beta_1 \ln P_{rt} + \beta_2 \ln Y_{irt} + \beta_3' \mathbf{X} + \upsilon_{irt} \tag{2.1}$$

where subscript i denotes household, r denotes region and t denotes month. Q_{irt} is the number of alcoholic units purchased, P_{rt} is the mean price per unit paid in region r at time t, and Y_{irt} is the total expenditure of the household. $\mathbf{X}$ is a matrix of control variables. Three variables are included to control for demographic characteristics: the (log) number of adults in the household,[3], the number of children in the household, and the age of the oldest household member. Regional and monthly differences in consumption are captured through fixed effects, and there is a linear time trend. υ_{irt} is a normally-distributed error term with mean zero. Because the model is double-log, β_1 can be directly interpreted as the price elasticity of demand for alcohol and β_2 can be directly interpreted as the expenditure elasticity of demand for alcohol. However, using Ordinary Least Squares, β_1 simply represents the mean elasticity. As mentioned in the in introduction, there are many reasons for wanting to know how β_1 varies over the distribution.

2.4.1.1 Conditional Quantile Regression

This chapter uses quantile regression, as used by Manning et al (1995) and Saffer et al (2012). Conditional quantile regression, as set out by Koenker and Basset (1978), minimises the weighted least absolute deviations using the formula

$$\min_{b_q}[\sum_{y_i \geq x_i b_q} q|y_i - x_i b_q| + \sum_{y_i \leq x_i b_q} (1-q)|y_i - x_i b_q|] \tag{2.2}$$

where b is the coefficient estimate and q is the quantile. Note that a least absolute deviation regression is a quantile regression with $q = 0.5$ such that positive and negative deviations are equally weighted. It should be clear from Equation 2.2 that, in conditional quantile regression, observations are weighted based on whether their observed outcome is above the predicted outcome. In a regression with a single, binary explanatory variable,

$$b_q = F_Y^{-1}(q|X=1) - F_Y^{-1}(q|X=0) \tag{2.3}$$

[3]The number of adults is logged to allow for non-linear household size effects.

such that, say, b_{25} is the difference between the lower quartiles of the two conditional distributions.

2.4.1.2 Unconditional Quantile Regression

Firpo et al (2009) present an alternative to the conditional quantile regression method using the recentered influence function (RIF). Beginning with a single binary regressor for simplicity, unconditional quantile regression differs from conditional quantile regression in that it estimates $dq_\tau(x)/dx$ - the effect of a unit increase on the τth quantile of the unconditional distribution. In unconditional quantile regression, this is found as

$$dq_\tau(x)/dx = (Pr[Y > q_\tau|X = 1] - Pr[Y > q_\tau|X = 0])/f_Y(q_\tau) \tag{2.4}$$

which is the difference in the proportion of each subgroup having a value greater than the quantile of the unconditional distribution, divided by the frequency density at the quantile of the unconditional distribution. The main advantage of the RIF is that it satisfies the properties: firstly, that its mean is the same as the observed quantile

$$\mathrm{E}_Y[RIF(Y, q_\tau)] = q_\tau \tag{2.5}$$

and secondly that the mean of the conditional expectation is equal to the observed quantile

$$\mathrm{E}_X\{\mathrm{E}_Y[RIF_Y, q_\tau)|X]\} = q_\tau \tag{2.6}$$

The linear regression model can be written as

$$RIF(Y, q_\tau = X\beta + \varepsilon \tag{2.7}$$

where β is equal to the partial effect: $\mathrm{E}[d\mathrm{E}[RIF(Y, q_\tau)|X]/dx]$ (Nicoletti and Best, 2012). A good summary of the differences between conditional and unconditional quantile regression, applied to medication adherence, is provided in Borah and Basu (2013).

The main advantage of unconditional quantile regression over conditional quantile regression is that it attempts to estimate the 'true' effect of a variable on the dependent variable, rather than the effect of a variable on the *expected* dependent variable conditional on other explanatory variables. This could be seen as more important for policy, since it is heavy drinkers *regardless of other characteristics* which policymakers care more about.

2.4.2 Quality and Unit Prices

It is important to consider quality as another mechanism by which consumers can respond to price increases. Consumers can maintain quantity given price changes by changing quality. This is true of both price increases and price decreases - drinks manufacturers may hope consumers trade up to higher price items when prices fall. Throughout this work, quality is represented through higher per-unit prices.

The work on quality is based upon Deaton (1988), which in turn builds on seminal work by Houthakker and Prais (1952) and Prais and Houthakker (1955). Deaton (1988) uses clusters, which for the purpose of this work will be regional areas r at a specific time t. Price variation is assumed to not occur within a cluster - such that all individuals in region r at time t face the same price. Firstly, then, the unit value is calculated by dividing expenditure by quantity

$$V_{irt} = \frac{X_{irt}}{Q_{irt}} \tag{2.8}$$

where V_{irt} is the mean price-per-unit paid by household i in region r at time t, X_{irt} is the total expenditure on alcohol by household i in region r at time t, and Q_{irt} is the number of alcoholic units purchased by household i in region r at time t. If expenditure is written as

$$X_{irt} = P_{rt} Q_{irt} q_{irt} \tag{2.9}$$

where P_{rt} is the cluster-level price index as described in the data section, Q_{irt} is the quantity purchased by household i in region r at time t, and q_{irt} denotes a quality scalar, then it can be shown that the unit price depends on the price index P_rt and also the quality element chosen by each household. Substituting Equation 2.9 into Equation 2.8 gives

$$V_{irt} = \frac{X_{irt}}{Q_{irt}} = \frac{P_{rt}Q_{irt}q_{irt}}{Q_{irt}} = P_c q_{irt} \tag{2.10}$$

which shows that the unit value is the product of true price, and a quality element which households choose. As with Deaton (1988), the logarithm can be taken so that

$$\ln V_{irt} = \ln P_{rt} + \ln q_{irt} \tag{2.11}$$

The quality elasticity can be found by differentiating Equation 2.11 with respect to $\ln P_{rt}$,

$$\frac{\delta \ln V_{irt}}{\delta \ln P_{rt}} = \frac{\delta \ln P_{rt}}{\delta \ln P_{rt}} + \frac{\delta \ln q_{irt}}{\delta \ln P_{rt}} \tag{2.12}$$

which gives

$$\frac{\delta \ln V_{irt}}{\delta \ln P_r t} = 1 + \varepsilon_{q_{irt}} \tag{2.13}$$

where $\varepsilon_{q_{irt}}$ is the price elasticity of quality demanded. This says that as price increases by 1%, quality increases by $(1+\varepsilon_{q_{ic}})\%$. It is expected that $\varepsilon_{q_{ic}}$ will be negative, such that consumers are expected to absorb some price increase by switching to lower quality alternatives. The regression equation is then

$$\ln V_{irt} = \alpha + \beta_1 \ln P_{rt} + \beta_2 \ln Y_{irt} + \beta_3' \mathbf{X} + \upsilon_{irt} \tag{2.14}$$

The price elasticity of quality demanded is thus $(\beta_1 - 1)$. If no quality substitution takes place then $\beta_1 = 1$. It is also expected that β_2 is positive, such that households with higher incomes will purchase higher quality alcohol. The variable matrix $\mathbf{X}$ comprises the same variables as Equation 2.1.

To find how the price elasticity of quality demanded varies over the drinking distribution, conditional quantile regression is used but the weights are the same weights as in the quantity regression.

2.5 Results

2.5.1 Quantity - Conditional Quantile Regression

The regression results for total alcohol consumption are shown in Table 2.2. For brevity, only the lower quartile, median, upper quartile, 90^{th} and 95^{th} percentiles are shown. Region dummies are omitted from the table. Figure 2.6 shows the estimated price elasticity across the drinking distribution.

It is clear that heavier drinkers' demand for alcohol is less elastic than moderate drinkers'. The difference between the lower and upper quartile is significantly different from zero. However, unlike Manning et al. (1995) and Saffer et al. (2012), the price elasticity is always significantly different from zero - although only by a small amount. It is also clear from Figure 2.6 that the OLS estimate is only representative of the middle of the drinking distribution, underestimating the price elasticity of light drinkers and overestimating the price elasticity of heavy drinkers. The expenditure elasticity is close to constant across the drinking distribution.

It is perhaps not surprising that alcohol expenditure increases most in November and December, but it is perhaps interesting to note that this effect is greater in the lighter drinkers. This pattern seems to be observed in every month, with heavy drinkers showing less seasonal variation in their consumption than lighter drinkers. This makes sense since there will be several people who only tend to drink around holiday times, whereas heavy drinkers drink all year round. It is also interesting that the parameter associated with the logarithm of the number of adults in the household is less than one - meaning each additional adult reduces per-capita consumption. Age of the oldest household member is predicted to be negatively related to the level of household consumption in OLS, but this is shown to differ across the drinking distribution, with the heavy drinking younger households drinking more than heavy drinking older households.

Elasticities are also separately estimated for on- and off-premise alcohol, with the results presented in Table 2.3 and Table 2.4 respectively. The results are shown graphically in Figure 2.7 and Figure 2.8. The pattern is still similar, with heavy drinkers having less elastic demand, but not to the same extent as the 'all alcohol' model. For on-premise alcohol, the elasticity estimated using OLS fits the majority of the distribution. It is interesting to observe that the cross-price elasticity for on- and off-premise alcohol is mostly insignificant, although OLS predicts a large and significant cross-price elasticity for off-premise alcohol. This is true in the quantile regression estimates for the lower quantiles, suggesting that on- and off-premise alcohol are substitutes for the lighter drinkers. Of course, this refers to light *off-premise* drinkers rather than light drinkers, so that is perhaps why the cross-price elasticity is only significant in terms of changing the quantity of off-premise alcohol.

Table 2.2: Price Elasticity of Quantity Demanded: All Alcohol

Dep Var: Log Units		Quantile				
	OLS	25	50	75	90	95
Log Price	-0.542	-0.693	-0.489	-0.352	-0.242	-0.147
	(0.035)***	(0.057)***	(0.044)***	(0.037)***	(0.041)***	(0.045)***
Log Total Per-Capita Expenditure	0.388	0.396	0.432	0.427	0.391	0.374
	(0.010)***	(0.016)***	(0.012)***	(0.011)***	(0.011)***	(0.013)***
Log Number of Adults	0.733	0.799	0.776	0.707	0.638	0.590
	(0.014)***	(0.023)***	(0.018)***	(0.015)***	(0.016)***	(0.018)***
Number of Children	-0.073	-0.094	-0.074	-0.066	-0.058	-0.054
	(0.006)***	(0.010)***	(0.008)***	(0.006)***	(0.007)***	(0.008)***
Age of Oldest Hhold Member	-0.001	-0.004	-0.000	0.002	0.003	0.004
	(0.000)***	(0.001)***	(0.000)	(0.000)***	(0.000)***	(0.000)***
February	0.108	0.145	0.107	0.135	0.099	0.095
	(0.028)***	(0.046)***	(0.035)***	(0.030)***	(0.032)***	(0.036)***
March	0.107	0.102	0.094	0.125	0.128	0.099
	(0.027)***	(0.045)**	(0.035)***	(0.029)***	(0.032)***	(0.036)***
April	0.135	0.169	0.138	0.160	0.095	0.034
	(0.027)***	(0.044)***	(0.034)***	(0.029)***	(0.031)***	(0.035)
May	0.136	0.171	0.128	0.145	0.133	0.130
	(0.027)***	(0.045)***	(0.034)***	(0.029)***	(0.032)***	(0.036)***
June	0.149	0.199	0.151	0.144	0.142	0.139
	(0.027)***	(0.044)***	(0.034)***	(0.029)***	(0.031)***	(0.035)***
July	0.149	0.188	0.147	0.124	0.117	0.131
	(0.027)***	(0.044)***	(0.034)***	(0.029)***	(0.031)***	(0.035)***
August	0.156	0.196	0.148	0.139	0.141	0.069
	(0.027)***	(0.044)***	(0.034)***	(0.029)***	(0.031)***	(0.035)**
September	0.106	0.147	0.098	0.113	0.110	0.056
	(0.027)***	(0.044)***	(0.034)***	(0.029)***	(0.031)***	(0.035)
October	0.109	0.142	0.113	0.119	0.102	0.052
	(0.027)***	(0.044)***	(0.034)***	(0.029)***	(0.031)***	(0.035)
November	0.209	0.246	0.192	0.196	0.224	0.210
	(0.026)***	(0.044)***	(0.034)***	(0.028)***	(0.031)***	(0.035)***
December	0.366	0.427	0.347	0.340	0.343	0.335
	(0.027)***	(0.045)***	(0.035)***	(0.029)***	(0.032)***	(0.036)***
Linear Time Trend	-0.001	-0.001	-0.001	-0.001	-0.001	-0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)*
Constant	1.102	0.412	1.003	1.601	2.291	2.683
	(0.067)***	(0.110)***	(0.085)***	(0.072)***	(0.079)***	(0.088)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Region fixed effects included. Observations: 47,082.

Table 2.3: Price Elasticity of Quantity Demanded: On-Premise Alcohol

Dep Var: Log On-Premise Units		Quantile				
	OLS	25	50	75	90	95
Log On-Premise Price	-0.487	-0.570	-0.533	-0.423	-0.292	-0.193
	(0.040)***	(0.061)***	(0.056)***	(0.055)***	(0.058)***	(0.064)***
Log Off-Premise Price	0.042	0.113	0.098	0.039	-0.047	-0.161
	(0.069)	(0.104)	(0.096)	(0.093)	(0.099)	(0.110)
Log Total Per-Capita Expenditure	0.154	0.166	0.159	0.181	0.159	0.203
	(0.012)***	(0.019)***	(0.017)***	(0.017)***	(0.018)***	(0.020)***
Log Number of Adults	0.705	0.789	0.843	0.752	0.570	0.508
	(0.017)***	(0.025)***	(0.024)***	(0.023)***	(0.024)***	(0.027)***
Number of Children	-0.153	-0.157	-0.174	-0.168	-0.154	-0.151
	(0.007)***	(0.011)***	(0.010)***	(0.010)***	(0.011)***	(0.012)***
Age of Oldest Hhold Member	-0.011	-0.014	-0.014	-0.009	-0.006	-0.004
	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
February	0.060	0.074	0.056	0.077	0.101	0.004
	(0.033)*	(0.050)	(0.046)	(0.045)*	(0.048)**	(0.053)
March	0.051	0.038	0.050	0.055	0.137	0.066
	(0.033)	(0.049)	(0.046)	(0.044)	(0.047)***	(0.052)
April	0.092	0.113	0.139	0.071	0.086	0.053
	(0.032)***	(0.048)**	(0.045)***	(0.043)	(0.046)*	(0.051)
May	0.058	0.056	0.079	0.061	0.061	0.029
	(0.032)*	(0.049)	(0.045)*	(0.044)	(0.047)	(0.052)
June	0.018	-0.007	0.018	0.051	0.076	0.044
	(0.032)	(0.048)	(0.045)	(0.043)	(0.046)	(0.051)
July	0.068	0.033	0.117	0.074	0.089	0.020
	(0.032)**	(0.048)	(0.044)***	(0.043)*	(0.046)*	(0.051)
August	0.092	0.084	0.109	0.112	0.116	0.021
	(0.032)***	(0.048)*	(0.044)**	(0.043)***	(0.046)**	(0.051)
September	0.035	0.037	0.052	0.051	0.029	-0.019
	(0.032)	(0.048)	(0.044)	(0.043)	(0.046)	(0.051)
October	0.005	-0.038	0.016	0.050	0.083	0.019
	(0.032)	(0.049)	(0.045)	(0.044)	(0.046)*	(0.051)
November	0.030	0.027	0.033	0.044	0.067	0.027
	(0.032)	(0.048)	(0.045)	(0.043)	(0.046)	(0.051)
December	0.082	0.112	0.106	0.058	0.131	0.058
	(0.033)**	(0.050)**	(0.046)**	(0.045)	(0.047)***	(0.053)
Linear Time Trend	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Constant	2.411	1.744	2.587	3.066	3.548	3.448
	(0.107)***	(0.162)***	(0.149)***	(0.146)***	(0.154)***	(0.171)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Region fixed effects included. Observations: 31,559.

Table 2.4: Price Elasticity of Quantity Demanded: Off-Premise Alcohol

Dep Var: Log Off-Premise Units		Quantile				
	OLS	25	50	75	90	95
Log On-Premise Price	0.095	0.126	0.102	0.044	0.027	0.071
	(0.033)***	(0.053)**	(0.045)**	(0.042)	(0.048)	(0.053)
Log Off-Premise Price	-0.721	-0.936	-0.768	-0.513	-0.388	-0.270
	(0.058)***	(0.092)***	(0.078)***	(0.074)***	(0.083)***	(0.093)***
Log Total Per-Capita Expenditure	0.334	0.337	0.359	0.363	0.335	0.322
	(0.010)***	(0.016)***	(0.013)***	(0.012)***	(0.014)***	(0.016)***
Log Number of Adults	0.473	0.455	0.534	0.564	0.525	0.502
	(0.014)***	(0.022)***	(0.019)***	(0.018)***	(0.020)***	(0.023)***
Number of Children	-0.023	-0.028	-0.023	-0.020	-0.025	-0.026
	(0.006)***	(0.010)***	(0.008)***	(0.008)***	(0.009)***	(0.010)***
Age of Oldest Hhold Member	0.005	0.004	0.005	0.006	0.007	0.006
	(0.000)***	(0.001)***	(0.001)***	(0.000)***	(0.001)***	(0.001)***
February	0.119	0.167	0.125	0.119	0.118	0.076
	(0.029)***	(0.045)***	(0.038)***	(0.036)***	(0.041)***	(0.046)*
March	0.093	0.126	0.125	0.078	0.098	0.041
	(0.028)***	(0.045)***	(0.038)***	(0.036)**	(0.041)**	(0.045)
April	0.096	0.121	0.106	0.121	0.078	-0.017
	(0.028)***	(0.044)***	(0.037)***	(0.035)***	(0.040)**	(0.044)
May	0.111	0.135	0.105	0.136	0.141	0.129
	(0.028)***	(0.044)***	(0.037)***	(0.035)***	(0.040)***	(0.044)***
June	0.136	0.200	0.147	0.120	0.122	0.107
	(0.027)***	(0.043)***	(0.037)***	(0.035)***	(0.039)***	(0.044)**
July	0.108	0.110	0.134	0.104	0.121	0.085
	(0.027)***	(0.043)**	(0.037)***	(0.035)***	(0.039)***	(0.044)*
August	0.104	0.121	0.105	0.108	0.112	0.052
	(0.027)***	(0.043)***	(0.037)***	(0.035)***	(0.039)***	(0.044)
September	0.071	0.067	0.098	0.091	0.093	0.021
	(0.027)***	(0.043)	(0.037)***	(0.035)***	(0.039)**	(0.044)
October	0.099	0.103	0.120	0.106	0.074	0.011
	(0.027)***	(0.043)**	(0.037)***	(0.035)***	(0.039)*	(0.044)
November	0.208	0.231	0.206	0.196	0.234	0.200
	(0.027)***	(0.042)***	(0.036)***	(0.034)***	(0.039)***	(0.043)***
December	0.369	0.408	0.385	0.381	0.379	0.358
	(0.027)***	(0.043)***	(0.036)***	(0.034)***	(0.039)***	(0.043)***
Linear Time Trend	-0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.000)**	(0.000)	(0.000)*	(0.000)	(0.000)	(0.000)
Constant	0.591	-0.288	0.429	1.243	2.010	2.575
	(0.089)***	(0.142)**	(0.120)***	(0.114)***	(0.129)***	(0.144)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Region fixed effects included. Observations: 35,901.

Figure 2.6: Price Elasticity of Quantity Demanded: All Alcohol

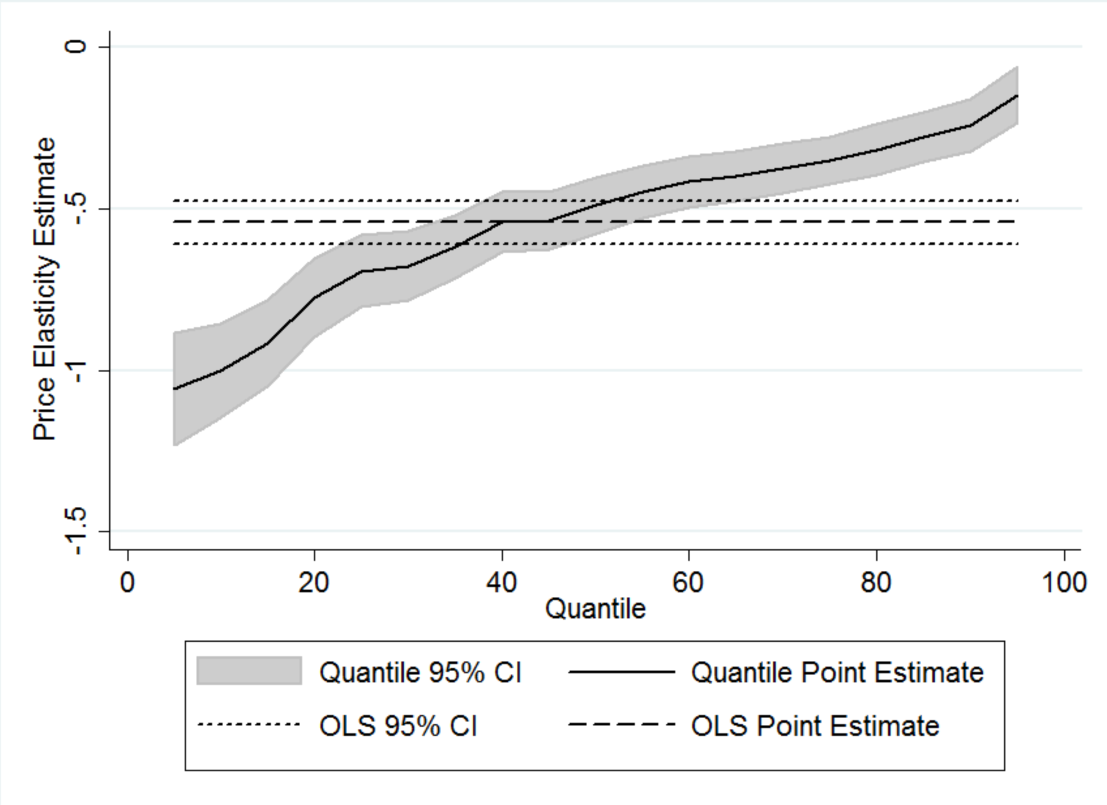


Figure 2.7: Price Elasticity of Quantity Demanded: On-Premise Alcohol

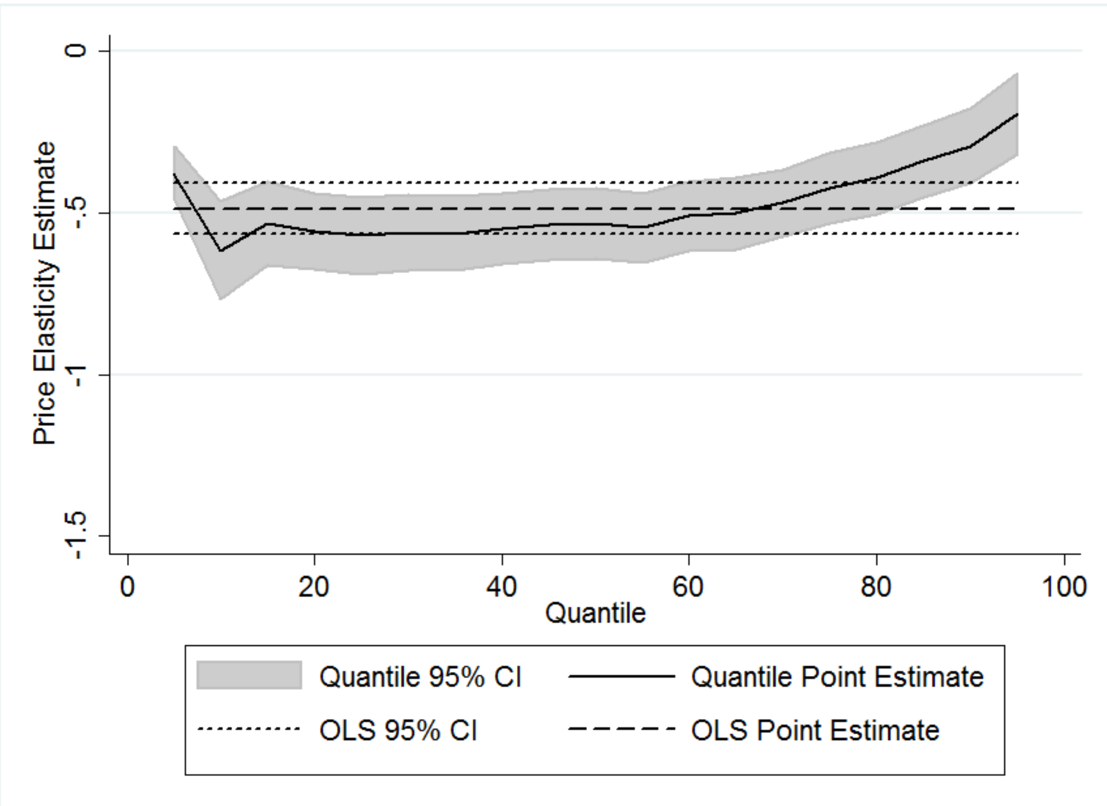
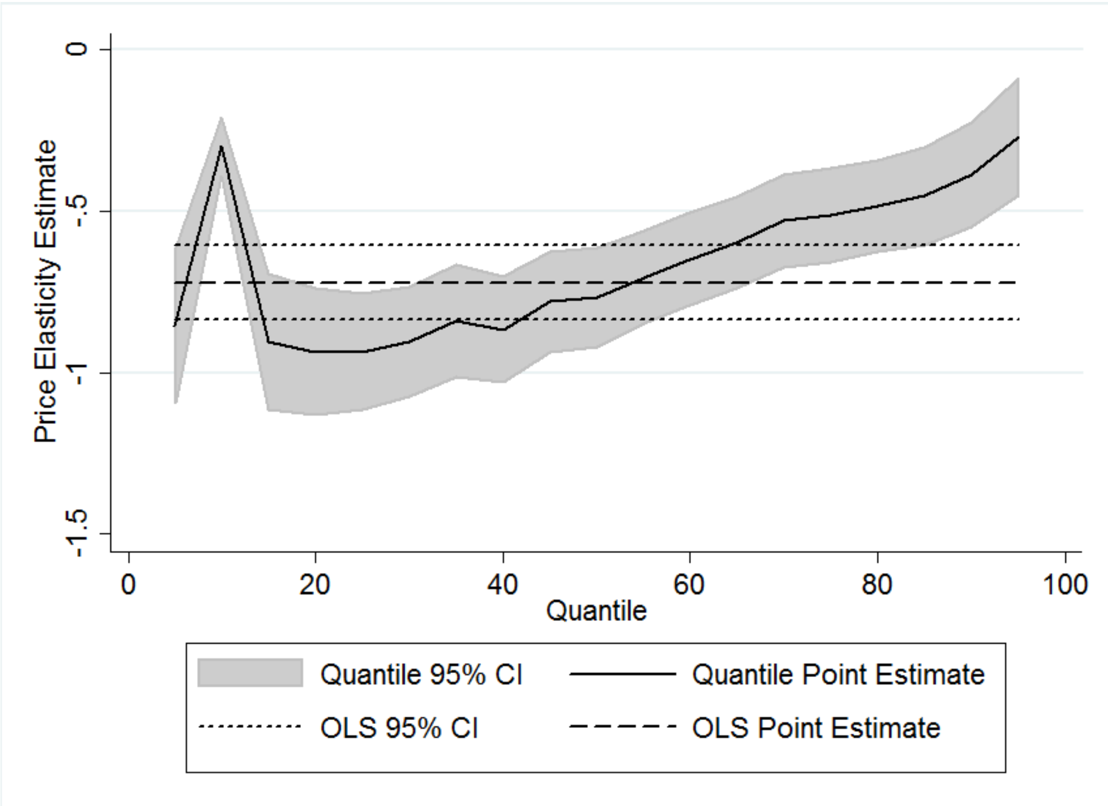


Figure 2.8: Price Elasticity of Quantity Demanded: Off-Premise Alcohol



2.5.2 Quantity - Unconditional Quantile Regression

Table 2.5 and Figure 2.9 show the results from the unconditional quantile regression. The elasticity estimates do not appear to be substantially different from the conditional quantile regression. Heavy drinkers are still found to have the least elastic demand, with an estimated elasticity for the upper quartile of -0.28. The results of the conditional and unconditional quantile regressions are compared in Table 2.6. It is interesting that the elasticity estimates do not differ substantially between conditional and unconditional quantile regression, and this is because all other coefficients are relatively stable across the distribution. If, say, being a male had a large differential effect across the distribution, then we might expect a difference between conditional and unconditional quantile regression parameter estimates.

Table 2.5: Price Elasticity of Quantity Demanded: All Alcohol

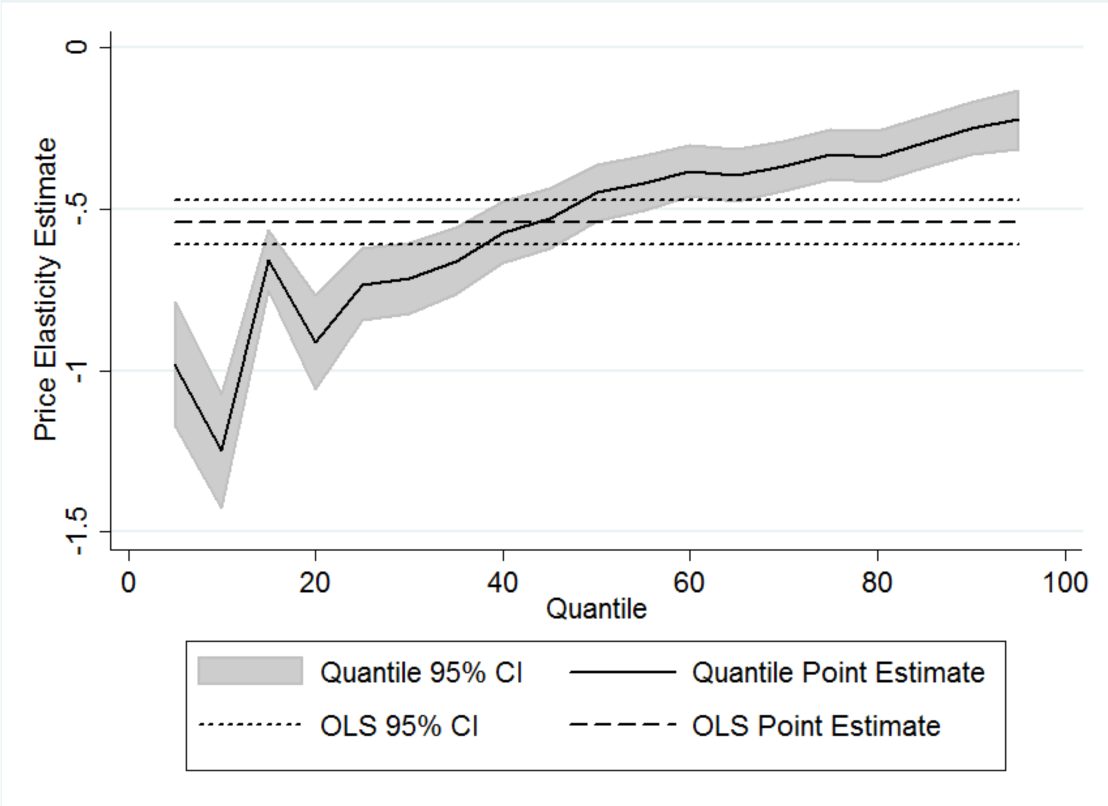
Dep Var: Log Units		Quantile				
	OLS	25	50	75	90	95
Log Price	-0.542	-0.733	-0.449	-0.329	-0.248	-0.223
	(0.035)***	(0.057)***	(0.045)***	(0.039)***	(0.041)***	(0.047)***
Log Total Per-Capita Expenditure	0.388	0.419	0.457	0.408	0.344	0.311
	(0.010)***	(0.017)***	(0.012)***	(0.011)***	(0.012)***	(0.014)***
Log Number of Adults	0.733	0.788	0.827	0.713	0.616	0.555
	(0.014)***	(0.023)***	(0.017)***	(0.015)***	(0.017)***	(0.020)***
Number of Children	-0.073	-0.092	-0.083	-0.070	-0.056	-0.055
	(0.006)***	(0.010)***	(0.008)***	(0.007)***	(0.007)***	(0.009)***
Age of Oldest Hhold Member	-0.001	-0.004	-0.001	0.001	0.003	0.002
	(0.000)***	(0.001)***	(0.000)**	(0.000)***	(0.000)***	(0.000)***
February	0.108	0.169	0.115	0.119	0.081	0.042
	(0.028)***	(0.047)***	(0.036)***	(0.030)***	(0.030)***	(0.034)
March	0.107	0.144	0.097	0.118	0.123	0.075
	(0.027)***	(0.047)***	(0.036)***	(0.030)***	(0.030)***	(0.034)**
April	0.135	0.154	0.142	0.156	0.065	0.016
	(0.027)***	(0.046)***	(0.035)***	(0.030)***	(0.029)**	(0.032)
May	0.136	0.154	0.112	0.139	0.119	0.075
	(0.027)***	(0.046)***	(0.035)***	(0.030)***	(0.030)***	(0.034)**
June	0.149	0.215	0.148	0.141	0.162	0.068
	(0.027)***	(0.045)***	(0.035)***	(0.029)***	(0.030)***	(0.033)**
July	0.149	0.201	0.132	0.127	0.131	0.076
	(0.027)***	(0.045)***	(0.035)***	(0.029)***	(0.029)***	(0.033)**
August	0.156	0.190	0.154	0.146	0.138	0.069
	(0.027)***	(0.045)***	(0.035)***	(0.029)***	(0.030)***	(0.033)**
September	0.106	0.129	0.099	0.114	0.083	0.042
	(0.027)***	(0.045)***	(0.035)***	(0.029)***	(0.029)***	(0.032)
October	0.109	0.145	0.117	0.116	0.085	0.015
	(0.027)***	(0.045)***	(0.035)***	(0.029)***	(0.029)***	(0.032)
November	0.209	0.247	0.194	0.207	0.205	0.178
	(0.026)***	(0.044)***	(0.034)***	(0.030)***	(0.031)***	(0.036)***
December	0.366	0.360	0.358	0.383	0.420	0.400
	(0.027)***	(0.044)***	(0.035)***	(0.031)***	(0.034)***	(0.041)***
Linear Time Trend	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Constant	1.102	0.238	0.929	1.816	2.676	3.219
	(0.067)***	(0.113)**	(0.084)***	(0.073)***	(0.079)***	(0.091)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Region fixed effects included. Observations: 47,082.

Table 2.6: Comparison of Conditional and Unconditional Quantile Regressions

	OLS	Conditional Quantile			Unconditional Quantile		
	mean	25	50	75	25	50	75
Log Price	-0.542	-0.693	-0.489	-0.352	-0.733	-0.449	-0.329
	(0.035)***	(0.057)***	(0.044)***	(0.037)***	(0.057)***	(0.045)***	(0.039)***

Figure 2.9: Price Elasticity of Quantity Demanded: All Alcohol



2.5.3 Quality

The price elasticity of quality demanded is estimated across the drinking distribution by weighting a median regression using the same weights used in the conditional quantile regressions for quantity section. The results are presented in Table 2.7 and graphically in Figure 2.10. It is important to remember that the price elasticity of quality demanded is calculate as $(\beta - 1)$, such that a lower co-efficient in Table 2.7 implies more elastic demand for quality. As expected, the total expenditure elasticity (β_2 in Equation 2.14) is positive. The price-per-unit is lowest in December, because of discounting in major stores. It is perhaps interesting that the effect of December is fairly constant across the drinking distribution - it is not just the light drinkers who are paying less.

Since the quantity regressions used the average price per unit paid within each month-region cell, this removed the quality element from the price measure. To complete the findings presented in this chapter, Figure 2.11 shows the estimated price elasticity of demand if unit prices are allowed to differ by individual households. It is clear that the price elasticity estimates do not substantially differ across the distribution, and this is because quality is biasing the price elasticity estimate.

Table 2.7: Price Elasticity of Quality Demanded: All Alcohol

Dep Var: Unit Value (V_{irt})		Quantile				
	OLS	25	50	75	90	95
Log Price	0.578	0.698	0.504	0.369	0.324	0.296
	(0.017)***	(0.026)***	(0.022)***	(0.019)***	(0.018)***	(0.017)***
Log Total Per-Capita Expenditure	0.211	0.196	0.212	0.220	0.241	0.268
	(0.005)***	(0.007)***	(0.006)***	(0.006)***	(0.005)***	(0.005)***
Log Number of Adults	0.141	0.143	0.181	0.166	0.160	0.159
	(0.007)***	(0.011)***	(0.009)***	(0.008)***	(0.007)***	(0.007)***
Number of Children	-0.097	-0.110	-0.115	-0.110	-0.097	-0.095
	(0.003)***	(0.005)***	(0.004)***	(0.003)***	(0.003)***	(0.003)***
Age of Oldest Hhold Member	-0.005	-0.005	-0.006	-0.007	-0.006	-0.005
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
February	-0.020	-0.030	-0.036	-0.022	0.002	0.000
	(0.014)	(0.021)	(0.018)**	(0.016)	(0.014)	(0.014)
March	-0.006	-0.028	-0.033	-0.013	0.010	-0.010
	(0.014)	(0.021)	(0.017)*	(0.015)	(0.014)	(0.014)
April	-0.012	-0.056	-0.032	-0.016	0.006	0.033
	(0.013)	(0.020)***	(0.017)*	(0.015)	(0.014)	(0.013)**
May	-0.009	-0.030	-0.040	-0.025	0.006	-0.003
	(0.013)	(0.021)	(0.017)**	(0.015)	(0.014)	(0.014)
June	-0.023	-0.051	-0.053	-0.022	0.002	-0.008
	(0.013)*	(0.020)**	(0.017)***	(0.015)	(0.014)	(0.013)
July	-0.021	-0.059	-0.054	-0.043	-0.016	-0.005
	(0.013)	(0.020)***	(0.017)***	(0.015)***	(0.014)	(0.013)
August	-0.018	-0.056	-0.042	-0.025	-0.009	-0.003
	(0.013)	(0.020)***	(0.017)**	(0.015)*	(0.014)	(0.013)
September	-0.006	-0.045	-0.025	-0.022	0.019	0.024
	(0.013)	(0.020)**	(0.017)	(0.015)	(0.014)	(0.013)*
October	-0.029	-0.073	-0.054	-0.030	0.008	0.026
	(0.013)**	(0.020)***	(0.017)***	(0.015)**	(0.014)	(0.013)*
November	-0.047	-0.096	-0.087	-0.067	-0.050	-0.040
	(0.013)***	(0.020)***	(0.017)***	(0.015)***	(0.014)***	(0.013)***
December	-0.066	-0.129	-0.112	-0.101	-0.087	-0.091
	(0.013)***	(0.021)***	(0.017)***	(0.015)***	(0.014)***	(0.014)***
Linear Time Trend	0.002	0.002	0.002	0.002	0.001	0.001
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Region fixed effects included. Observations: 47,082.

Figure 2.10: Price Elasticity of Quality Demanded

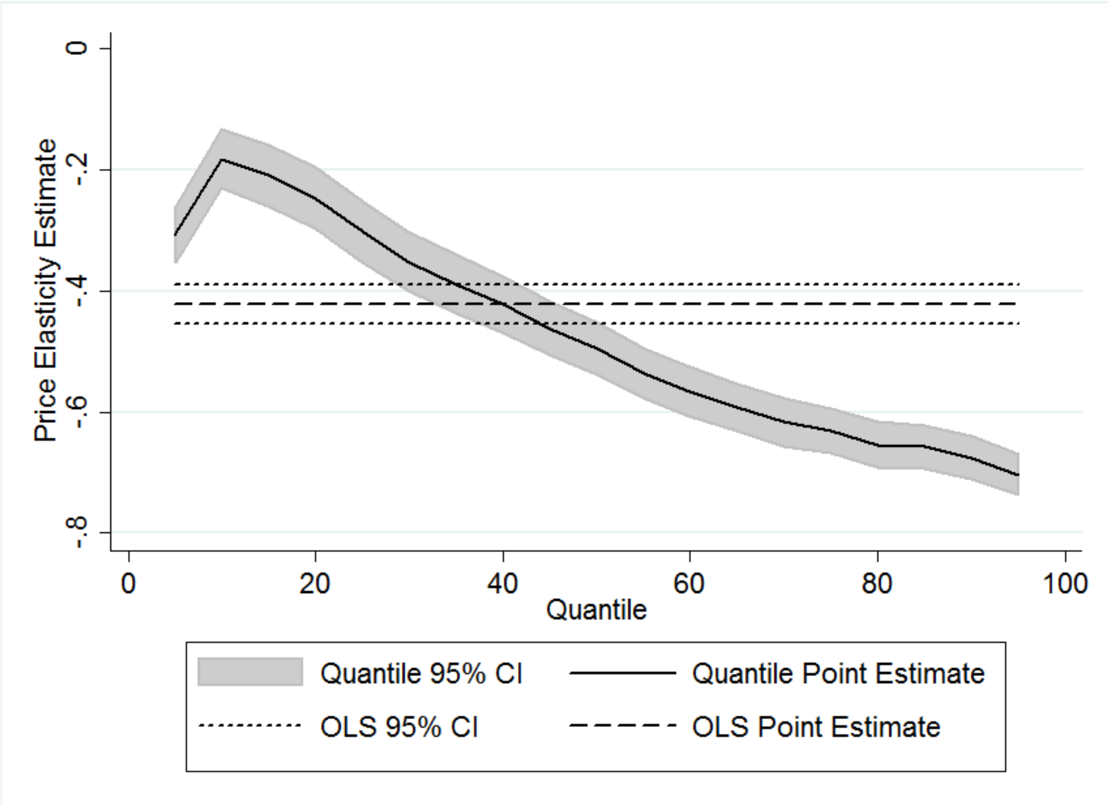
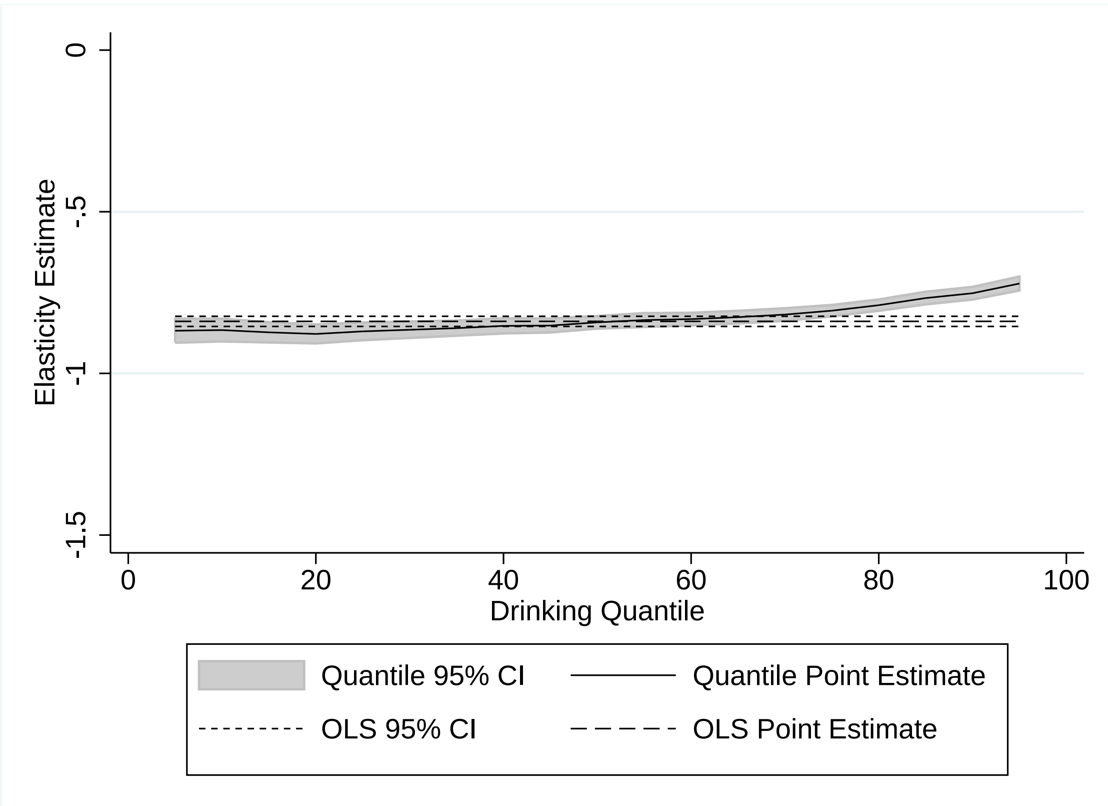


Figure 2.11: Price Elasticity of Demand: All Alcohol



2.6 Discussion

The results here seem plausible, and the OLS estimate for the price elasticity of demand for all alcohol (found in Table 2.2) lies within the range of the estimates found in the existing literature. The results presented in this chapter show convincingly that heavier drinkers are less responsive to price than moderate drinkers, especially for off-premise alcohol. The relative difference in price elasticity is most notable in Figure 2.6, and this is because the heaviest drinkers are in the top of the drinking distribution for both on- and off-premise alcohol. They also show that heavier drinkers respond to price increases by substituting towards cheaper alcohol. This suggests that lighter drinkers are more brand loyal and do not choose their alcoholic beverages based on the alcohol content. Meanwhile, heavy drinkers switch to cheaper per-unit alcoholic beverages when price increases.

This is an important finding - the quantity results show that price-based measures will have little effect in reducing heavy consumption because of their small absolute price elasticity, whilst simultaneously having a large negative effect on consumer surplus for the light drinking majority, because of their large absolute price elasticity.

2.6.1 Implications for Minimum Pricing

The work presented in this chapter is a significant contribution to the literature, especially in the debate around minimum unit pricing (MUP). Modelling work on the implications of MUP has assumed that either heavy drinkers were more responsive to price (Purshouse et al, 2010) or at least as responsive (Holmes et al, 2014) as moderate drinkers. Given the findings in this chapter, both modelling studies are likely to overestimate the health gains caused by minimum pricing. This problem is compounded if it is assumed, as in the modelling work, that the marginal effect of each alcohol unit on health increases with consumption. The results from this study show that price increases will have a weaker effect on heavier drinkers than on moderate drinkers, so price-based alcohol policies may not be the best method of tackling heavy drinking. That said, although the proportionate response is smaller for heavier drinkers - if price goes up by 10% the heaviest drinkers reduce consumption by 1.7% compared to 8% for moderate drinkers - the absolute number of units consumed decreases most for the heaviest drinkers. The 90th percentile of drinkers consumes 40 units per week, compared to 4.5 units for the lower quartile. Modelling a 10% price increase using the elasticities generated in this study show that the lower quartile reduce their consumption by roughly 14 units per year, whilst the 90th percentile reduce their consumption by 27 units per year. Again, assuming that the marginal effect of a unit of alcohol increases with consumption, this reduction of 27 units may bring great health benefits.

Purshouse et al. (2010) estimate that a 10% general price increase causes a 3.5% reduction in consumption for moderate drinkers, compared to a reduction of 4.7% and 4.5% for hazardous and harmful drinkers respectively. This, they claim, would lead to an increase of roughly 21,000 quality-adjusted life years (QALYs) per year in the population, the majority of which are from hazardous and harmful drinkers. Comparing the elasticity used (-0.45) with the estimate found in this study (-0.2) suggests that the health effect stated is likely double the true health effect, and potentially more if the relationship between consumption and harms is non-linear.

The results also show that heavy drinkers respond to price increases by switching to lower quality alcohol. This can either be in the form of switching from on-premise alcohol consumption to off-premise alcohol consumption (where the unit value is lower), or by switching from one brand of drink to another cheaper alternative. Whilst this makes little difference to health policy, unless of course lower quality alcohol is worse for health, it has a major implication in the effect of price increases. If the heaviest drinkers absorb price increases by substituting towards lower quality alcohol, then price increases are less effective. Minimum Unit Pricing, which sets a floor price, may eliminate the possibility of absorbing price increases by switching to lower quality alcohol. However, there is already likely to be a lower bound to quality which means that the ability to absorb price increases by switching to lower quality alcohol is limited.

2.6.2 Limitations of the Study

There are several limitations to this study. Firstly, because the dataset is a household-level survey it may not include those such as the homeless, the institutionalised or the armed forces, who may have different drinking habits and preferences to the dataset sample. Secondly, the fact that the data is collected at the household level means that assumptions must be made regarding the intra-household allocation of alcohol. Even though individual-level expenditure diaries are recorded, this is not sufficient due to intra-household transfers. This study thus implicitly assumes that alcohol purchased within a household is split evenly. This limitation is not seen as severe however, as this assumption is not necessary when estimating the price elasticity of demand for alcohol. The individual-level price elasticity of demand should not differ substantially from the household-level price elasticity. That said, there may be cases where a household appears in the upper 5% of drinking households, whilst a very heavy drinker living in a large house with non-drinkers may not be included in the upper 5% of drinking households. This is perhaps unlikely to happen in a large amount of households because it relies on the other members of the household not drinking. Data from the General Household Survey 2006, which records average weekly consumption through an interview, reveals that an individual's alcohol consumption and the consumption of others in the household is significantly correlated ($R^2 = 0.33, p < 0.001$). Another limitation due to the dataset, as has already been discussed in the previous chapter, is infrequent purchase and stockpiling. This may mean that some households are counted as heavy drinking households even though their consumption may not match expenditure in the two-week period. This is simply measurement error and there is no way of telling whether the household is stockpiling or not. Any other dataset would have similar measurement error problems, and so this limitation is hard to avoid.

Another possible limitation is under-recording of consumption. Alcohol consumption is known to be under-recorded in surveys when compared to aggregate clearance data (see, for a good review, Boniface and Shelton (2013)). Under-reporting is also seen in other areas such as labour market in terms of unemployment (see, for example, van den Berg et al (2006) on survey non-response bias). However, unlike in van den Berg et al (2006), information on the demographic characteristics of non-repondents is not known. As long as under-reporting, or non-response, is not correlated with drinking, or that this correlation has not changed over time, then the results found in this study are valid. More evidence is needed on under-reporting before this issue can be addressed.

Another potential problem is assessing whether the change in unit values after a general price increase is due to consumer choice, as used in this study, or whether the change is due to suppliers absorbing some of the price increase. To understand this, one would need to estimate the price elasticity of supply, and how this differs by differing quality alcohol type. Work by Ally et al (2014), using quantile regression to analyse price data from supermarket shelves, shows that tax increases are not passed through consistently across the distribution. In particular, cheaper beverages absorb taxation whereas more expensive beverages pass through taxation by more than 1. This may present a problem in this analysis because this work assumes that it is the individual drinkers making a decision about quality. If, instead, their drink prices are not increasing as much as other drink prices, then this effect may be exaggerated. Better, more detailed information on the exact product being purchased would give a better indicator of whether they are truly substituting to lower quality products. The finding of Ally et al (2014) introduces an interesting conundrum. Economic theory suggests that products with inelastic demand tend to absorb more of the tax increases, but this chapter finds that the heaviest drinkers (who tend to buy the cheaper products) have the most inelastic demand. It is likely that the supply elasticity is the key to solving this apparent conundrum.

2.6.3 Robustness Checks

Various robustness checks were carried out to test the stability of the results across different specifications. For example, the price variable was constructed without regional differences (the average price-per-unit for each time period), and no qualitative difference to the results was found. Similarly, using quarters instead of months makes no qualitative differences to the results.

Split-sample regressions were used to test whether there are heterogeneous results by other characteristics. For example, only households with one adult were included in the sample, and no qualitative difference to the results was found. This might be expected as the effect of the number of adults in the household was relatively stable in the original regressions. Using households with only one adult also removes any uncertainty about intra-household transfer.

2.6.4 Future Work

The work presented in this chapter is novel, and it has extended the literature.The work could be informed more through use of panel data on alcohol consumption which is not currently available. Another important extension would be work that examines the intra-household allocation of alcohol to better inform this study about which households are truly heavy drinking households. This work could compare expenditure surveys such as the one used in this study with health surveys which generally ask consumption-related questions such as the number of units of alcohol consumed in a typical week. Understanding intra-household transfer would be useful for all demand work using household expenditure surveys. Future work should also use the new estimates found in this chapter to re-assess the evidence for minimum unit pricing. Finally, estimating the price elasticity of supply, which is often overlooked in the literature, would provide a better understanding of the likely effects of policy.

Additional research could also use new techniques for including non-consumption into the econometric modelling, perhaps using censored quantile regression techniques. However, careful consideration would be needed when deciding on the model structure as non-consumption can occur for several different reasons.

2.7 Conclusions

This chapter has used conditional and unconditional quantile regression to estimate the price elasticity of demand for alcohol across the drinking distribution. Both conditional and unconditional quantile regression estimates predict that heavier drinking households are less responsive to price than moderate drinking households. If the price of alcohol increases by 10% then the top decile of drinkers reduce their consumption by 2.2% compared to 8.9% for the lowest decile. The results also show that, as price increases, heavier drinkers switch to lower quality alcohol more than moderate drinkers. This suggests that price-based policies may have little effect in reducing consumption at the top of the drinking distribution, and that modelling work which uses constant elasticities across the drinking distribution is likely to overstate the health gains of a price increase.

Chapter 3

The Demand for Alcohol: A Double-Hurdle Model with Abstention and Infrequency

3.1 Introduction

Alcohol is consumed by the majority of the UK adult population, but there is still a non-trivial and increasing amount of people who do not drink. Because of the link between alcohol and health, and because alcohol duty contributes a substantial amount of tax revenue, the price elasticity of demand for alcohol is an important parameter to estimate. However, estimating the elasticity is complicated by the presence of zeros in micro-level expenditure survey data which is commonly used. The contribution of this chapter is to compare different techniques for modelling alcohol demand with zero observations, using a novel predictor of abstention and also using the price variable constructed in the previous chapter.

Zero expenditure can occur for three distinct reasons. Firstly, an individual may be willing to purchase alcohol, but economic factors - prices and income - mean that they do not. In this case, a lower price or higher income would result in expenditure being observed. Secondly, an individual may conscientiously abstain from purchasing alcohol because of health, social or religious reasons. This individual would not purchase alcohol even if the price was zero. Finally, because expenditure surveys typically rely on a small time period to record expenditure, infrequent purchase may lead to some typical alcohol purchasers not being observed to purchase alcohol in the survey.

This chapter begins with a summary of the existing literature on alcohol demand, before reviewing the labour supply literature which can often have the same problem of zero observations for different reasons. It then discusses the methodological techniques used in the literature in more detail. The data is described, before presenting and discussing the results from the various modelling techniques. It finds that the estimate of the price elasticity of demand is fairly stable across model specifications, except the Tobit model which produces a larger absolute estimate of price and income elasticities. Implications of these findings are discussed.

3.2 Literature Review

3.2.1 Alcohol Demand

Many papers have estimated the demand for alcohol. A meta-analysis of 132 studies by Gallet (2007) finds a median price elasticity of demand of -0.535, but notes that model specification can cause large variation in the results. Similarly, a meta-analysis by Wagenaar et al (2009) finds a mean price elasticity of demand of -0.44. Since Gallet (2007) does not report the mean price elasticity, yet both papers review largely the same papers, it is unclear why the median and mean are so different.

Many studies have attempted to model the demand for alcohol using micro-level expenditure data because the richness of data allows for more detailed analysis. Atkinson et al (1990) use data from the UK Family Expenditure Survey, and fit a gamma-Tobit model. The gamma-Tobit model relaxes the assumption of normality in the error term - the Tobit is developed from the Probit model which assumes a normally-distributed error term[1]. They find an average price elasticity of -1.1, which seems very elastic compared to the existing literature. This may be because the Tobit, and the gamma-Tobit extension, essentially assumes that the participation and consumption decision are formed with the same underlying mechanism.

Yen and Jensen (1996) fit a double-hurdle model to analyse the determinants of alcohol demand, although price elasticities are not estimated and price does not feature as an explanatory variable. To allow for zeros in the data, whilst also accounting for heteroscedasticity and non-normality, the dependent variable is transformed using the inverse hyperbolic sine (IHS) transformation. The transformation is similar to taking the logarithm of the dependent variable, but under the IHS transformation zero is defined. The authors compare the double-hurdle model to the Tobit model, and highlight several notable differences between the model results. Some of the resulting elasticities have large differences. It finds that the composition of the household is an important characteristic of household demand for alcohol. For example, the number of children reduces the demand for alcohol, whilst younger households purchase more alcohol *ceteris paribus*. The authors also find some regional differences in the demand for alcohol, and suggest that this could be used for targeted taxation in the United States. Finally, the authors call for more data on alcohol expenditure with price data included.

Collis et al (2010) is an HMRC study on the demand for alcohol in the United Kingdom. It estimates the demand for 10 different alcoholic drinks (beer, wine, cider, spirits, ready-to-drink (RTD); on- and off-premise) separately, without estimating the demand for the aggregated commodity alcohol. The number of separate equations used means a greater number of households with zero expenditure, and the reason for the zero is less clear. The authors use the UK Expenditure and Food Survey, which collects data on quantity and expenditure. This can be used to create a unit value, by dividing expenditure by quantity; in this case the authors use price per millilitre for each drink type.

[1]The Gamma-Tobit was developed by Gomulka and more detail can be found in Gomulka (1986)

The authors allow the price variable to differ across households within the same region and time period, which will capture quality differences as well as true exogenous price variation. There is also little relative price variation between drink types in the survey period which may make it hard to identify meaningful cross-price elasticities, especially when quality variation is included in the price measure. The Tobit model is used, and households who do not purchase alcohol are assigned the mean price for their region, year and household size. There is also the problem that zeros are accounted for equally: the authors cannot identify whether a household would purchase, say, beer at a low price (in a Tobit-type manner) or not consume wine at any price (in an abstention-type manner). Furthermore, each demand model is run separately rather than using a systems-based approach such as the seemingly-unrelated Tobit model. This would not account for correlated error terms. The authors discuss the use of the double-hurdle model, but rule it out due to lack of an exclusion restriction in the data. The results show rather large elasticities, with the price elasticities for on-premise spirits, off-premise beer, and off-premise cider all with an elasticity greater than 1. This is surprising given that the demand for beer is often found to be the least elastic in the meta-analyses. The demand for off-premise beer does have several significant cross-price elasticities, some of which are surprising. For example, on- and off-premise beer are found to be complements, whilst almost all off-premise alcohol types are also found to be complements. The only significant substitute for off-premise beer is on-premise wine, which seems highly unlikely.

Sousa (2014) is a new HMRC study on the demand for alcohol. The difference between this and Collis et al (2010) is that it uses the Heckman selection model, which assumes that all zero observations are caused by abstention and that price does not play a role in causing zero observations. Sousa (2014) uses the Living Costs and Food Survey, from 2007 to 2012. As in Collis et al (2010), the demand for 10 different drink types is estimated. The price variable is again a unit value calculated by dividing expenditure by quantity, with the price for non-purchasing households again imputed based on the year, region and household size. The same caveat applies as in Collis et al (2010) that this will largely capture quality variation across purchasing households. Another criticism of this method is that the number of observations of, say, households purchasing on-premise ready-to-drink is likely to be very small and there will be a high level of measurement error and unobserved heterogeneity driving the relative price variation. Again, no systems-based approach is adopted, with each demand equation estimated separately. The study finds very different elasticities compared to Collis et al (2010), with the majority of the new elasticity estimates being around half as elastic, suggesting that model specification can cause large changes to the elasticities.

Finally, Meng et al (2014a) uses the Expenditure and Food Survey to create a pseudo-panel. The advantage of a pseudo-panel is that it eliminates some of the underlying unobserved heterogeneity that is present in repeated cross-sectional data. Membership of each pseudo-panel member cell is based on five-year birth cohort, gender and socioeconomic status, resulting in 72 panel member cells. The dependent variable is the average number of units consumed by the cell in each time period. Price is calculated as the mean unit value for each cell in each time period, where the unit value is household expenditure on each alcoholic drink divided by the number of alcoholic units of the corresponding alcoholic drink purchased. The analysis is run for the same 10 different drink types as Collis et al (2010) and Sousa (2014). Control variables include average cell income, the proportion of individuals having children, being married, being unemployed, and smoking. Random-effects and fixed-effects models are both run, and a Hausman test suggests that the fixed-effects model is the more appropriate specification. Meng et al (2014a) estimate 100 separate own- and cross-price elasticities, which is a large number of parameters (parameters are also estimated for several control variables), and the study may therefore have little predictive power. The own-price elasticities range from -1.268 (off-premise cider) to -0.082 (off-premise spirits). The majority (84 of 90) of cross-price elasticity estimates are insignificant at the 5% level, suggesting that aggregation is feasible. There are also some surprising elasticity estimates - one cross-price elasticity suggests that if the price of off-premise beer increases by 10%, the consumption of on-premise ready-to-drink increases by 5%, although this is not statistically significant. Significant cross-price elasticities are found for off-wine/off-cider, off-RTD/on-spirit, on-beer/on-wine on-beer/on-spirits, and on-spirits/on-RTD. No elasticity is calculated for an overall increase in the price of all alcoholic drink. There are several issues which this study does not fully deal with. The first is that the pseudo-panel method eliminates all zeros from the data when it creates the cell average, explicitly not allowing for zero consumption decisions. There is no mechanism by which an individual can stop consuming alcohol, and is instead assumed to decrease consumption. No modelling is done of prevalence elasticities. Secondly, the issue of allowing quality to vary across pseudo-panel members over time means that any variation in unit value may be driven by quality rather than exogenous price variation. If heavier drinking pseudo-panel members switch to lower quality products, then their response to price increases will be exaggerated.

Overall, the literature on alcohol demand has not dealt adequately with the issue of zeros in expenditure data. The literature tends to either aggregate consumption, assuming that infrequent purchase is the only reason for zeros, or uses a single-hurdle method such as the Tobit model which does not fully allow for the three distinct reasons for zero expenditure.

3.2.2 Zeros in the Dependent Variable

There is a large amount of literature on female labour supply, which traditionally has a lot of zeros in the number of hours worked by women. As with alcohol demand, some of these zeros arise because the wage offered is below the reservation wage - this would be dealt with by using the Tobit model. However, there are some women who are removed from the potential labour market through active choice, and these would not work at any wage rate. It should be clear that this is analagous to the demand for alcohol; the former group (those not working because the wage rate is below the reservation wage) similar to those who would drink at lower prices, and the latter group (those removed from the labour market) similar to abstainers. Alternatively in the employment literature, there may be some people who do not want to work because the wage rate is too low and some people who do not work - despite being willing to work at the current wage level - because they cannot find employment. Notable examples of work on female labour supply include Blundell, Ham and Meghir (1987) which extends the labour supply model to include involuntary unemployment. Two good reviews are provided by Heckman (1993) and Blundell and MaCurdy (1999).

Aside from labour supply, several papers have estimated demand for products which have many potential non-purchasers. Farell and Walker (1999) estimate the demand for lotto, using a Tobit specification, a Heckman selection model, and a censored least absolute deviations (CLAD) estimator, which is essentially a Tobit-type extension of Least Absolute Deviation (quantile regression at the median). The Heckman selection model is useful because it allows the participation and consumption decisions to be modelled separately. However the model also requires an exclusion restriction[2] - a variable which does not feature in both the participation and consumption decision - and the variable chosen by the authors (car ownership to predict participation) is perhaps a little weak. They find larger total price and income elasticities in the Tobit model than in either OLS or the Heckman Selection Model.

Newman et al (2001) run an infrequent purchase model (the p-Tobit) and a double-hurdle model to estimate meat expenditure in Irish households. They use the inverse hyperbolic sine to transform the dependent variable, which allows for heteroscedasticity and a non-normal error structure. The authors omit economic factors from the first hurdle since this is predicting abstention from meat purchasing: it is assumed there exist some households who would not purchase certain types of meat, or any meat, at any price or income. However, they do not include price in the regressions. Although the

[2]Technically, the model can be fitted without an exclusion restriction, but only through the nonlinearity of hte inverse Mills ratio.

study estimates expenditure for several types of meat, and includes a dummy variable to indicate which other types of meat a household purchased, there is no indication how the relationship between the error terms - which are likely to be correlated - are handled.

Carroll et al (2005) use the double-hurdle model to estimate the amount households donate to charity, and compare this to results generated by the Tobit model. The authors also compare the standard Tobit model with a Tobit model using the inverse hyperbolic sine transformation of the dependent variable. The decision of which variable appears in each hurdle appears arbitrary. For example, month is not included in participation but is included in the expenditure decision. On no occasion does a variable have a different direction of magnitude in the participation and expenditure decisions. For example, those who have more disposable income are more likely to give, and - when they give - give more. However, it is found that the double-hurdle model captures the process of charitable giving better than the Tobit.

Aristei and Pieroni (2008) model the demand for tobacco using a double-hurdle model. As with Newman et al (2001) and Carroll et al (2005), the error terms in each hurdle are assumed to be independent from each other.

As with Newman, the study excludes non-economic factors from the analysis. Because it uses only one wave of the Italian Household Budget Survey, the study assumes that there is no price variation, and thus no price elasticity can be calculated. Some coefficients differ in direction for participation and consumption, such as whether the respondent owns their own property. This increases the probability of smoking, but decreases the conditional amount smoked. Conversely, having children makes a respondent less likely to smoke but smoke more if they do smoke. This shows the advantage of the double-hurdle over the Tobit model, which would restrict the model to display the same direction on the signs of both participation and consumption.

Infrequent purchase is the motivation behind Keen (1986), which develops the p-Tobit model by multiplying observed expenditure by observed probability of purchase. An example used is a household purchasing £1 of cigarettes every two days, but recording a one-day expenditure diary. Here, the observed expenditure is £1 and the probability of purchase is 50%, giving the true expected daily cigarette expenditure as £0.50. However, as Pudney (1989) correctly critiques the model, empirical estimation rests upon non-purchasers being representative of purchasers, with the only difference being infrequent purchase. In effect, then, there is no abstention in the model. Whilst this may be true of certain expenditures, such as food and haircuts, this is unlikely to be true for alcohol. There is also the problem that those observed purchasing a good or service may be more likely to purchase the item more frequently, and also spend more.

3.3 Methods

3.3.1 Unconditional OLS

Running ordinary least squares in the presence of a large number of zero observations would result in inconsistent and biased estimates. This is because the majority of zeros in expenditure data are not true zeros - many arise because of infrequency, and some households would be willing to purchase alcohol at a lower price or higher income. It is done in this study only for illustrative and comparative purposes.

3.3.2 Conditional OLS

It is possible to run regressions using only those households who purchased alcohol in the survey period. The estimates would be unbiased if, and only if, the purchasing subsample is not any different to the consuming sample. In this case, price plays no part in determining participation. This could either be due to abstention or infrequency, but only if purchase infrequency is not related to price. Unconditional OLS is done in this study to compare with more sophisticated techniques.

3.3.3 Tobit Model

The Tobit model (Tobin, 1958) is a commonly-used technique to deal with censored dependent variables. It is a combination of two steps - a Probit model to determine participation in the alcohol market, and a linear regression to model the consumption level. In the Tobit model, both decisions are jointly determined by the same underlying process. Formally, the Tobit model uses the latent variable y^* and the observed variable y. The latent variable is assumed to be linear such that

$$y_i^* = \beta' x_i + \varepsilon_i \tag{3.1}$$

where the error term, ε_i, is assumed to be normally distributed[3]. The observed variable is defined as

$$y_i = \max(y_i^*, 0) \tag{3.2}$$

The log-likelihood function for the Tobit model can be written as

$$\ln L = \sum_{y_i = y_i^*} -\frac{1}{2}[ln(2\pi) + ln\theta^2 + \frac{(y_i - \beta X_i)^2}{\theta^2}] + \sum_{y_i=0} \ln[1 - \Phi(\frac{\beta X_i}{\theta})] \tag{3.3}$$

where it should be clear that $\beta' x_i$ is determining both the Probit participation (the first section on the right-hand side) and the maximum likelihood linear model (the second section on the right-hand side). McDonald and Moffitt (1980) provide a useful decomposition of the marginal effect of the Tobit model to show that

$$\frac{\partial E[y_i|x_i]}{\partial x_i} = \text{prob}[y_i \geq 0] \frac{\partial E[y_i|x_i, y_i \geq 0]}{\partial x_i} + E[y_i|x_i, y_i \geq 0] \frac{\partial \text{prob}[y_i \geq 0]}{\partial x_i} \tag{3.4}$$

3.3.4 P-Tobit Model

The P-Tobit model is a mechanism designed by Deaton and Irish (1984) to model infrequent purchase. Its name is derived from the Tobit model, but with an additional

[3]The gamma-Tobit, as used by Atkinson et al (1990) allows for a non-normal distribution in the error term, but still has the restrictive assumption that the participation and consumption decisions are jointly determined.

feature which is a constant term to predict the probability of observing purchase. The underlying process of the model is

$$\begin{aligned} y_i &= (y_i^* + \upsilon_i)/P_i \qquad \text{if } D_i \geq 0 \\ y_i &= 0 \qquad\qquad\qquad \text{otherwise} \end{aligned} \tag{3.5}$$

where

$$D_i = z_i \cdot \theta + w_i \tag{3.6}$$

If w_i $N(0,1)$ then $P_i = \Phi(z_i \cdot \theta)$ as shown in Blundell and Meghir (1987). Assuming that $P = P_i$ as done in Maki and Nishiyama (1996), the log-likelihood function can be written as

$$\ln L = \sum_0 \ln(1 - P\Phi(X_i'\beta/\sigma)) - (n_+/2)\ln\sigma^2 + n_+ \ln P + \sum_+ \ln\phi((y_i - X_i'\beta)/\sigma) \tag{3.7}$$

It should be noted that the p-Tobit model collapses to the conventional Tobit model when $P_i = P = 1$.

3.3.5 The Double-Hurdle Model

The Double-Hurdle model is based on work by Cragg (1971), which is an alternative extension of the Tobit model. As the name suggests, the underlying process requires two hurdles to be cleared before purchase is observed. This can be written as two latent variables

$$\begin{aligned} y_i^* &= X_{1i}'\beta + \varepsilon_i \\ z_i^* &= X_{2i}'\gamma + \upsilon_i \end{aligned} \tag{3.8}$$

where the observed variable y is defined as

$$\begin{aligned} y_i &= y_i^* \qquad \text{if } y_i^* \geq 0 \text{ and } z_i^* \geq 0 \\ y_i &= 0 \qquad\ \text{otherwise} \end{aligned} \tag{3.9}$$

The error terms ε_i and υ_i are assumed to be normally distributed with mean zero and variance of σ^2 and 1 respectively. The first equation is the latent consumption decision, which still behaves as a conventional Tobit. The second equation is a latent binary participation decision, which allows for both abstention and, under certain assumptions, infrequent purchase. It is possible for the error terms to be correlated to form the dependent double-hurdle. In this case the error terms are jointly distributed as

$$(\varepsilon_i, \upsilon_i) \sim N(0, \omega) \qquad \omega = \begin{bmatrix} \sigma^2 & \rho \\ \rho & 1 \end{bmatrix} \tag{3.10}$$

The assumption of dependent error terms can be tested against the independent double-hurdle model by testing the hypothesis that $\rho = 0$. The log-likelihood for the double-hurdle model can be written as in Garcia (2013) as

$$\begin{aligned} \ln L = &\textstyle\sum_{y_i=0} \ln(1 - [\Phi(X'_{2i}\gamma)\Phi(X'_{1i}\beta/\sigma, \rho)) \\ &+ \textstyle\sum_{y_i>0} \left(\ln \Phi \frac{X_{2i}\gamma + \frac{\rho}{\sigma}(y_i - X_{1i}\beta)}{\sqrt{1-\rho^2}} - \ln\sigma + \ln\left[\phi\left(\frac{y_i - X_{1i}\beta}{\sigma}\right)\right] \right) \end{aligned} \tag{3.11}$$

The double-hurdle model collapses to the p-Tobit when $\Phi(X'_{2i}\gamma) = P_i = P$. Following from this, the double-hurdle thus collapses to the conventional Tobit model when $\Phi(X'_{2i}\gamma) = P_i = P = 1$.

To identify the double-hurdle model, it is useful to have some exclusive elements in the vectors X_{1i} and X_{2i}. Abstention should not be affected by price; any zeros arising from prices being too high feature in the participation decision. For this reason, price and income are usually excluded from the participation equation. Similarly, a variable needs to be used in just the binary participation decision - a variable which does not then explain the amount of alcohol purchased, conditional on being a potential purchaser.

3.3.6 Variables

All models use units of alcohol on the right-hand-side, transformed using the inverse-hyperbolic sine transformation (IHS). The independent variables included are: the mean price-per-unit of alcohol in each quarter-region cell; the total expenditure of the household; the log of the number of adults in the household; the number of children in the household; the age of the oldest household member; whether the household bought tobacco; whether the household purchased any gambling product; whether the household purchased any pork (or pork derivative including bacon and sausages); the interaction of gambling and pork expenditure (binary); the calendar quarter that the diary was recorded (to wash out seasonal effects); and a linear time trend.

3.4 Data and Summary Statistics

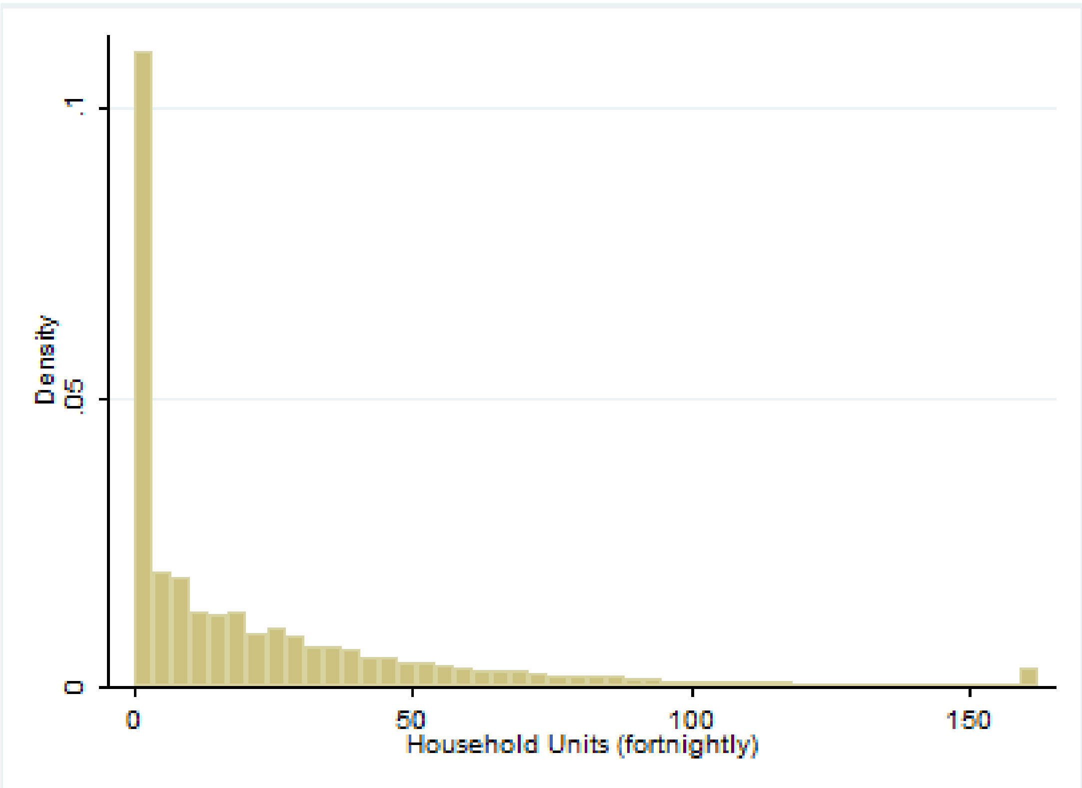
The data used in this study comes from the Expenditure and Food Survey (LFS) and its successor, the Living Costs and Food Survey (LCF), from 2001 to 2011 inclusive. The surveys are nationally representative surveys which ask randomly selected households to complete expenditure diaries for a two-week period. Each adult member of the household is required to complete an expenditure diary, but this study aggregates diaries to form household units because of the possibility of intra-household transfers. This also removes some doubt regarding zero expenditure - it could easily be the case that only one household member purchases alcohol for the entire household, causing a large number of zero observations and one large observed expenditure amount.

The dependent variable for this study is the number of units of alcohol purchased by the household within the diary period. The surveys record very disaggregated expenditure on alcohol type, for example “on-premise sparkling wine”. This study converts the quantity of each alcoholic drink into units of alcohol, where one unit of alcohol is equal to 10ml of pure ethanol, based on strength assumptions used in Purshouse et al (2010).

This chapter, and to some extent the previous chapter, estimate the demand for the composite commodity ‘alcohol’. The composite commodity theorem, presented in Hicks (1939), states that commodities can be aggregated if the prices of the goods change in the same proportion. Furthermore, and relevant for this chapter, modelling the demand for several disaggregated drink types - as done in Collis et al (2010), Sousa (2014) and Meng et al (2014a) - would result in a large number of zero observations, and the cause of these zeros is hard to distinguish. Without substantial relative price variation between drink types, it is difficult to identify any substitution effects. The results from the aforementioned studies show very small cross-price elasticities, suggesting that aggregation can be done without biasing the elasticity estimates. Aside from the difference between on-premise and off-premise alcohol, there has been little variation in relative prices across alcoholic beverages.

Even after aggregation across drinks and within households, there are a substantial number of households not observed to purchase any alcohol. Figure 3.1 shows the distribution of fortnightly expenditure on alcohol, where the data is truncated at the 99th percentile for easier viewing. Over 30% of households within the survey do not pur-

Figure 3.1: Fortnightly Expenditure on Alcohol, by Household



chase any alcohol. Comparing this to the General Household Survey (GHS) for 2006 suggests that the majority of non-purchasers are due to infrequent purchase. The GHS asks respondents how much they usually drink per week, rather than directly recording expenditure, so that infrequency is not possible except in extreme circumstances where very moderate drinkers round their consumption to zero. The GHS records 9% of households never drinking, which means that it would be expected that 20% of the EFS/LCF sample are infrequent purchasers rather than abstainers or classic Tobit-style corner solutions.

The dependent variable in this study is transformed using the inverse-hyperbolic sine transformation (IHS) used by Yen and Jensen (1996) for the reason that it allows for extreme values whilst preserving the zero observations. This transformation is used a great deal in other literature with similar dependent variable distributions (Yen and Su, 1996; Yen and Jones, 1997; Newman et al, 2001; Newman et al, 2003). The price variable used in this study is generated by calculating the mean unit value for all households in each region and quarter. This is similar to the method used by Collis et al (2010) and Sousa (2014), although all households within the region and quarter are expected to face this price rather than just the non-purchasing households. This removes endogeneity associated with quality variation across households. This regional price index is converted to real prices using the RPI inflation index for all items. The model includes total household expenditure as a separate covariate, allowing the calculation of the expenditure elasticity of demand for alcohol, which is equivalent to the income elasticity if expenditure and income are perfectly correlated. Other covariates in the model include the number of adults in the household, the number of children, the age of the oldest household member, and whether the household purchased tobacco. Quarterly dummies are included to capture seasonality, with a linear time trend also included. Regional dummies are used to allow the demand for alcohol to vary across regions, as well as controlling for price differences across regions.

To identify the double-hurdle model, an exclusion criteria needs to exist whereby the set of variables in the two hurdle equations are not identical. Formally, X_{1i} and X_{2i} in

Equation 3.8 should not be the same. Price and income should not feature in X_{2i}. Similarly, a predictor variable is needed which predicts possible (non-)participation in the alcohol market. A good variable would be religion, since alcohol is considered *Haram* (forbidden) in Islam. This means that Muslims would not participate in the alcohol market even if it was free. Unfortunately, religion is not included in the survey so it cannot be directly inserted into the model. Instead, expenditure on pork is used because pork is also considered *Haram*. However, Judaism also forbids pork, and vegetarians would also not purchase pork. Both of these groups may nevertheless consume alcohol. To add to the precision of the exclusion restriction, gambling expenditure is included because this is forbidden for Muslims but not for Jews or vegetarians. The interaction between the two gives even more precision, especially since gambling is a risky behaviour and may be correlated with greater alcohol expenditure. The assumption for the double-hurdle model is that purchasing neither pork nor gambling products means that the household is less likely to participate in the alcohol market, but given that it does, this does not affect the conditional level of alcohol expenditure.

Summary statistics are provided in Table 3.1, broken down into purchasing and non-purchasing households. 53% of non-drinking households did not purchase pork, compared to 38% of drinking households. Similarly, whether the household spent money on gambling is correlated with whether the household spent money on alcohol, with 93% compared to 84%. It is also worth noting that total expenditure is higher amongst households who purchased alcohol. Smoking status also differs, with 28% of drinking households spending money on tobacco products compared to 22% of non-drinking households.

Finally Table 3.2 shows the three key outcomes by household type. Of course, this is just the summary statistics and is not controlling for other explanatory variables such as the demographic composition of the household and crucially the price of alcohol.

Table 3.1: Summary Statistics

Variable	Non-Drinking Household	Drinking Household
Proportion of Households	32%	68%
Units (Household)	0	63.09
Per-Capita Total Expenditure	138.97	201.24
Number Adults	1.57	1.91
Number Children	0.54	0.59
Age of Oldest Hhold Member	56.09	51.36
Smoker	0.22	0.28
Quarter 1	0.26	0.22
Quarter 2	0.25	0.25
Quarter 3	0.26	0.26
Quarter 4	0.23	0.27
No Pork	0.53	0.38
No Gambling	0.93	0.84
No Pork and No Gambling	0.50	0.33

Table 3.2: Outcomes by Household Type

Household Type	% Buying Alcohol	Mean Units	Mean Units (U>0)
No Pork & No Gambling	58.5	30.1	50.9
Bought Pork, No Gambling	71.7	48.4	67.0
No Pork, Bought Gambling	78.4	50.3	63.4
Bought Both	85.8	70.7	82.0

3.5 Results

The results are presented in order of sophistication, beginning with the unconditional OLS results and finishing with the double-hurdle model. The model specification is built up in all cases, starting with a very simple model including just prices and total expenditure, and finishing with a full specification including all regressors.

3.5.1 Unconditional OLS

The results for the unconditional (i.e. including non-purchasing households) ordinary least squares model are presented in Table 3.3. The unconditional OLS is run only to show the most basic case.

3.5.2 Conditional OLS

The conditional (i.e. only purchasing households are included) OLS results presented in Table 3.4 are useful to observe the determinants of alcohol demand amongst households who were observed to purchase alcohol in the two-week period. That is, there is no participation effect at all.

It is clear from the difference between models (1) and (2) that introducing quarterly and regional dummies, and a linear time trend, reduces the price elasticitiy estimate, suggesting a high level of seasonality and regional variation. Interestingly, the expenditure elasticity is not greatly changed, and in fact stays relatively constant across the specifications.

The full specification estimates suggest that the number of adults in the household increases the demand for alcohol - which would be expected - but it is interesting that the elasticity is less than 1. This means that larger households purchase less alcohol per capita, *ceteris paribus*. The parameter estimate for the effect of the number of children is negative, which is expected given the result found in Yen and Jensen (1996). This is because households will allocate more of their budget to the children and less to alcohol. Smokers purchase more alcohol, conditional on being observed to purchase, which may be expected given their attitudes towards health and risk. Households who bought pork purchase significantly more alcohol, as do households who spent money on gambling activities. Crucially for this study, the effect of the interaction between pork and gambling expenditure is not significant.

It is worth comparing the difference between the conditional and unconditional OLS because this indicates the importance of a participation effect. For example, the interaction between pork and gambling expenditure is a significant predictor of the unconditional model. The fact that this variable is insignificant in the conditional model is encouraging for this study, since it suggests that the effect is in participation. Furthermore, the parameter estimate is negative.

3.5.3 Tobit Model

Results from the Tobit model are presented in Table 3.5. The Tobit model uses the same underlying process to model participation and consumption, which may be the reason why the price and expenditure elasticities are so much higher than the conditional OLS elasticity estimates. This is because it is assuming all zeros arise because of economic reasons. Once again, the addition of time and region variables reduces the price elasticity estimate, suggesting that there is large seasonal and regional variation driving the demand for alcohol.

All other parameter estimates are roughly as expected, although again the interaction between smoking and gambling is negative and significant. Comparing this to the uncondtional and conditional OLS results suggests that this is a good predictor of abstention rather than consumption.

Table 3.3: Unconditional OLS

Dep Var: Units (IHS transformed)	(1) Basic Model	(2) Time and Region Added	(3) Demographics	(4) Demographics	(5) Full
Log Real Price	-1.259***	-0.517***	-0.513***	-0.532***	-0.520***
	(0.0543)	(0.0875)	(0.0820)	(0.0821)	(0.0816)
Log Total Expenditure	1.150***	1.151***	1.140***	1.144***	1.109***
	(0.0128)	(0.0128)	(0.0128)	(0.0128)	(0.0128)
Linear Time Trend		-0.00554***	-0.00475***	-0.00427***	-0.00373***
		(0.000696)	(0.000653)	(0.000655)	(0.000652)
Log Number of Adults			1.508***	1.569***	1.465***
			(0.0192)	(0.0189)	(0.0192)
Number of Children			-0.281***	-0.273***	-0.282***
			(0.00855)	(0.00855)	(0.00851)
Age of Oldest Hhold Member			-0.00957***	-0.00849***	-0.0105***
			(0.000525)	(0.000521)	(0.000524)
Smoker			0.372***	0.392***	0.365***
			(0.0173)	(0.0173)	(0.0173)
No Pork			-0.428***		-0.293***
			(0.0157)		(0.0441)
No Gambling				-0.576***	-0.509***
				(0.0227)	(0.0278)
No Pork No Gambling					-0.140**
					(0.0468)
Constant	-3.250***	-2.770***	-2.740***	-2.574***	-2.126***
	(0.0680)	(0.0820)	(0.0919)	(0.0939)	(0.0959)
Observations	68564	68564	68564	68564	68564

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Parameters for Quarterly and Regional Dummies omitted for brevity

Table 3.4: Conditional OLS

Dep Var: Units (IHS transformed)	(1)	(2)	(3)	(4)	(5)
Log Real Price	-0.614***	-0.478***	-0.487***	-0.495***	-0.489***
	(0.0378)	(0.0602)	(0.0580)	(0.0581)	(0.0579)
Log Total Expenditure	0.325***	0.329***	0.405***	0.408***	0.399***
	(0.00946)	(0.00951)	(0.00969)	(0.00972)	(0.00971)
Linear Time Trend		-0.00260***	-0.00190***	-0.00180***	-0.00158***
		(0.000474)	(0.000458)	(0.000460)	(0.000458)
Log Number of Adults			0.660***	0.692***	0.648***
			(0.0139)	(0.0137)	(0.0140)
Number of Children			-0.0816***	-0.0755***	-0.0825***
			(0.00597)	(0.00597)	(0.00597)
Age of Oldest Hhold Member			-0.000665	-0.0000626	-0.000962*
			(0.000378)	(0.000376)	(0.000379)
Smoker			0.288***	0.296***	0.286***
			(0.0119)	(0.0119)	(0.0119)
No Pork			-0.182***		-0.195***
			(0.0111)		(0.0284)
No Gambling				-0.153***	-0.154***
				(0.0146)	(0.0177)
No Pork No Gambling					0.0176
					(0.0306)
Constant	2.380***	2.511***	1.795***	1.773***	1.964***
	(0.0516)	(0.0599)	(0.0679)	(0.0690)	(0.0702)
Observations	47082	47082	47082	47082	47082

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5: Tobit Model

Dep Var: Units (IHS transformed)	(1)	(2)	(3)	(4)	(5)
Log Real Price	-1.784***	-0.661***	-0.672***	-0.699***	-0.682***
	(0.0788)	(0.127)	(0.118)	(0.118)	(0.118)
Log Total Expenditure	1.691***	1.691***	1.675***	1.679***	1.631***
	(0.0191)	(0.0191)	(0.0190)	(0.0191)	(0.0190)
Linear Time Trend		-0.00728***	-0.00593***	-0.00527***	-0.00452***
		(0.00100)	(0.000939)	(0.000942)	(0.000937)
Log Number of Adults			2.122***	2.209***	2.060***
			(0.0279)	(0.0275)	(0.0279)
Number of Children			-0.400***	-0.386***	-0.401***
			(0.0123)	(0.0123)	(0.0122)
Age of Oldest Hhold Member			-0.0149***	-0.0133***	-0.0162***
			(0.000760)	(0.000754)	(0.000759)
Smoker			0.493***	0.520***	0.483***
			(0.0247)	(0.0247)	(0.0246)
No Pork			-0.604***		-0.312***
			(0.0226)		(0.0619)
No Gambling				-0.765***	-0.632***
				(0.0319)	(0.0388)
No Pork No Gambling					-0.316***
					(0.0658)
Constant	-6.683***	-5.979***	-5.859***	-5.669***	-5.065***
	(0.102)	(0.122)	(0.135)	(0.138)	(0.140)
sigma					
Constant	2.883***	2.873***	2.672***	2.675***	2.659***
	(0.0103)	(0.0103)	(0.00951)	(0.00952)	(0.00946)
Observations	68564	68564	68564	68564	68564

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.5.4 P-Tobit Model

The results from the p-Tobit, presented in Table 3.6 highlight the importance of modelling infrequent purchase. Comparing the results with the Tobit model, most of the parameter estimates are substantially smaller. For example, the expenditure elasticity estimate in the Tobit model is estimated at 1.631 compared to an elasticity in the p-Tobit model of just 0.417. The coefficient for the number of adults is also interesting, since the Tobit model estimated the elasticity at greater than 2. This implies that an additional household member is reflected in substantially greater per-capita alcohol expenditure. Under the p-Tobit model, this reduces to an elasticity of less than unity. The p-Tobit results also suggest that, whilst pork and gambling expenditure predict significantly less alcohol expenditure, the interaction is not significant. Finally, the fact that the constant in the participation equation is significantly different from zero suggests that the p-Tobit is significantly different from the Tobit model.

Table 3.6: p-Tobit

Dep Var: Units (IHS transformed)	(1)	(2)	(3)	(4)	(5)
Participation					
Constant	0.491***	0.490***	0.489***	0.489***	0.489***
	(0.00498)	(0.00498)	(0.00498)	(0.00497)	(0.00498)
Consumption					
Log Real Price	-0.514***	-0.333***	-0.337***	-0.344***	-0.340***
	(0.0341)	(0.0546)	(0.0522)	(0.0522)	(0.0522)
Log Total Expenditure	0.337***	0.338***	0.423***	0.427***	0.417***
	(0.00897)	(0.00902)	(0.00906)	(0.00907)	(0.00906)
Log Number of Adults			0.637***	0.667***	0.626***
			(0.0127)	(0.0125)	(0.0127)
Number of Children			-0.0743***	-0.0693***	-0.0749***
			(0.00532)	(0.00532)	(0.00532)
Age of Oldest Hhold Member			0.00155***	0.00213***	0.00134***
			(0.000352)	(0.000350)	(0.000352)
Smoker			0.269***	0.274***	0.267***
			(0.0107)	(0.0107)	(0.0107)
No Pork			-0.157***		-0.150***
			(0.0100)		(0.0254)
No Gambling				-0.120***	-0.113***
				(0.0130)	(0.0158)
No Pork No Gambling					-0.00658
					(0.0273)
Constant	3.134***	3.262***	2.369***	2.326***	2.493***
	(0.0491)	(0.0564)	(0.0631)	(0.0638)	(0.0650)
σ	1.624***	1.618***	1.563***	1.565***	1.561***
	(0.00761)	(0.00759)	(0.00723)	(0.00724)	(0.00722)
Covariance	-1.536***	-1.530***	-1.483***	-1.485***	-1.480***
	(0.00944)	(0.00942)	(0.00880)	(0.00881)	(0.00881)
Observations	68564	68564	68564	68564	68564

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.5.4.1 P-Tobit Marginal Effects

The marginal effects are presented for the P-Tobit models in Table 3.7. The table shows the marginal effect of price, which can be directly interpreted as the price elasticity of demand. The 'conditional' margin is the marginal effect of price on the expected number of units given that the respondent purchases alcohol, formally $\frac{\partial \mathrm{E}(y|x,y>0)}{\partial P}$. The 'total' margin is the marginal effect of price on the expected number of units purchased, formally $\frac{\partial \mathrm{E}(y|x)}{\partial P}$. These are estimated as set out in Garcia (2013).

Table 3.7: P-Tobit Marginal Effects

Marginal Effect	**Model**				
	(1)	(2)	(3)	(4)	(5)
Conditional	-0.506***	-0.328***	-0.332***	-0.339***	-0.335***
	(0.034	(0.054)	(0.051)	(0.051)	(0.051)
Total	-0.353***	-0.229***	-0.231***	-0.236***	-0.233***
	(0.023)	(0.037)	(0.036)	(0.036)	(0.036)

3.5.5 Double-Hurdle Model

The double-hurdle model is the final model presented in this chapter, and the results are shown in Table 3.8. It is an extension of the p-Tobit in that is has more explanatory variables in the participation equation to allow for both abstention and infrequency. The results of the full specification are of most interest, since it includes the most variables in the consumption equation. It is clear that the interaction between pork and gambling expenditure is a significant predictor of participation. By themselves, pork and gambling expenditure are also significant predictors of participation, but what is most striking is that they are significant predictors of consumption in the opposite direction than perhaps expected. Purchasing pork means that the household is expected to purchase less alcohol, given that they purchase alcohol at all. This may be because of substitution between pork and alcohol. Another interesting result omitted from the table demonstrates the advantage of the double-hurdle specification over the Tobit model. Some regional and quarterly dummies have opposite effects on participation and consumption, which the standard Tobit model does not allow for. Similarly, age has a negative effect on participation, but a positive effect on consumption.

The double-hurdle model predicts that 31% of the population are infrequent purchasers or abstainers, which is the substantial majority of the 32% of the sample who did not purchase alcohol.

Table 3.8: Double-Hurdle Model

Dep Var: Units (IHS transformed)	(1)	(2)	(3)	(4)
Participation				
Log Number of Adults	0.660***	0.701***	0.653***	0.636***
	(0.0128)	(0.0128)	(0.0128)	(0.0131)
Number of Children	-0.105***	-0.101***	-0.107***	-0.109***
	(0.00557)	(0.00557)	(0.00559)	(0.00561)
Age of Oldest Hhold Member	-0.0111***	-0.0105***	-0.0113***	-0.0116***
	(0.000340)	(0.000339)	(0.000342)	(0.000343)
Smoker	0.0430***	0.0533***	0.0415***	0.0411***
	(0.0114)	(0.0114)	(0.0114)	(0.0115)
No Pork	-0.229***			-0.177***
	(0.00813)			(0.0268)
No Gambling		-0.317***		-0.360***
		(0.0138)		(0.0194)
No Pork No Gambling			-0.275***	-0.0757**
			(0.00843)	(0.0271)
Constant	0.906***	1.014***	0.927***	1.246***
	(0.0343)	(0.0362)	(0.0344)	(0.0390)
Consumption				
Log Real Price	-0.372***	-0.386***	-0.384***	-0.387***
	(0.0535)	(0.0537)	(0.0536)	(0.0538)
Log Total Expenditure	0.401***	0.403***	0.397***	0.397***
	(0.00909)	(0.00911)	(0.00909)	(0.00912)
Log Number of Adults	0.0997***	0.105***	0.107***	0.132***
	(0.0169)	(0.0169)	(0.0169)	(0.0170)
Number of Children	0.00198	0.00295	0.000778	0.00268
	(0.00713)	(0.00712)	(0.00710)	(0.00710)
Age of Oldest Hhold Member	0.00966***	0.00963***	0.00950***	0.00977***
	(0.000448)	(0.000448)	(0.000446)	(0.000453)
Smoker	0.246***	0.244***	0.246***	0.249***
	(0.0143)	(0.0143)	(0.0142)	(0.0142)
No Pork				0.0379**
				(0.0132)
No Gambling				0.151***
				(0.0181)
Constant	2.163***	2.133***	2.175***	2.006***
	(0.0683)	(0.0683)	(0.0682)	(0.0715)
σ	1.470***	1.468***	1.462***	1.457***
	(0.00702)	(0.00711)	(0.00703)	(0.00708)
Covariance	-1.352***	-1.345***	-1.338***	-1.331***
	(0.00988)	(0.0101)	(0.0101)	(0.0103)
Observations	68564	68564	68564	68564

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.5.5.1 Double-Hurdle Marginal Effects

Table 3.9: Double Hurdle Marginal Effects

Marginal Effect	Model			
	(1)	(2)	(3)	(4)
Conditional	-0.369***	-0.383***	-0.381***	-0.384***
	(0.053)	(0.053)	(0.053)	(0.053)
Total	-0.255***	-0.265***	-0.263***	-0.265***
	(0.037)	(0.037)	(0.037)	(0.037)

3.6 Conclusion

This study has compared several different model specifications used in the alcohol demand literature to examine the difference in elasticity estimates. It has also used a novel variable - the interaction of pork and gambling expenditure - to predict abstention. This predictor allows for a full double-hurdle model to be run without dropping arbitrary variables from one equation to assist identification. The model allows for Tobit-style corner solutions, infrequent purchase and abstention. Results from the Tobit model are vastly different from any other of the model specifications which treat zero observations, suggesting that studies using the Tobit model such as Collis et al (2010) may be exaggerating the price elasticity of demand for alcoholic drinks. This is because the Tobit model assumes that all of the zero observations are caused by price and correspondingly overweights the importance of price. This is especially true of studies using expenditure surveys, where the majority of zeros are likely to be caused by infrequent purchase.

3.6.1 Limitations and Future Research

Of course, the data used only spans two weeks of expenditure records for each household. The problem of infrequency would be helped by a longer diary period, although this would likely cause a decrease in response rates. A panel dataset on expenditure may also help to solve the problem of infrequency, since it is effectively increasing the diary period. However, it would be hard with panel data to tell whether a household who purchased a good in one wave but not another did so because of infrequency or because of other demand-shifting reasons such as price. Future work could experiment by just using a single week's data from the Living Costs and Food Survey, testing how this changed the estimates and how well the infrequent purchase model picked up the (observed) infrequency in households who bought in the alternate week.

Another important caveat to this research is that pork and gambling expenditure are, in themselves, infrequently purchased goods. This will mean that the strength of the identification strategy is reduced because it is implictly assuming that infrequent pork purchasers are also less likely to purchase alcohol. It should not bias the estimates, however, and can simply be thought of as measurement error.

As with the previous chapter, the work presented in this chapter could be improved with a better understanding of intra-household transfers and individual consumption. Aggregating to the household level is necessary because there would be a large number of zeros due to intra-household transfer, which would complicate the analysis further. Attempting to estimate a double-hurdle model for all beverage categories, instead of aggregating them into a single commodity, is worth investigating in future research, although a suitable identification strategy is difficult to envisage.

Chapter 4

Heavy Drinking and the Life Course: A Synthetic Cohort Analysis

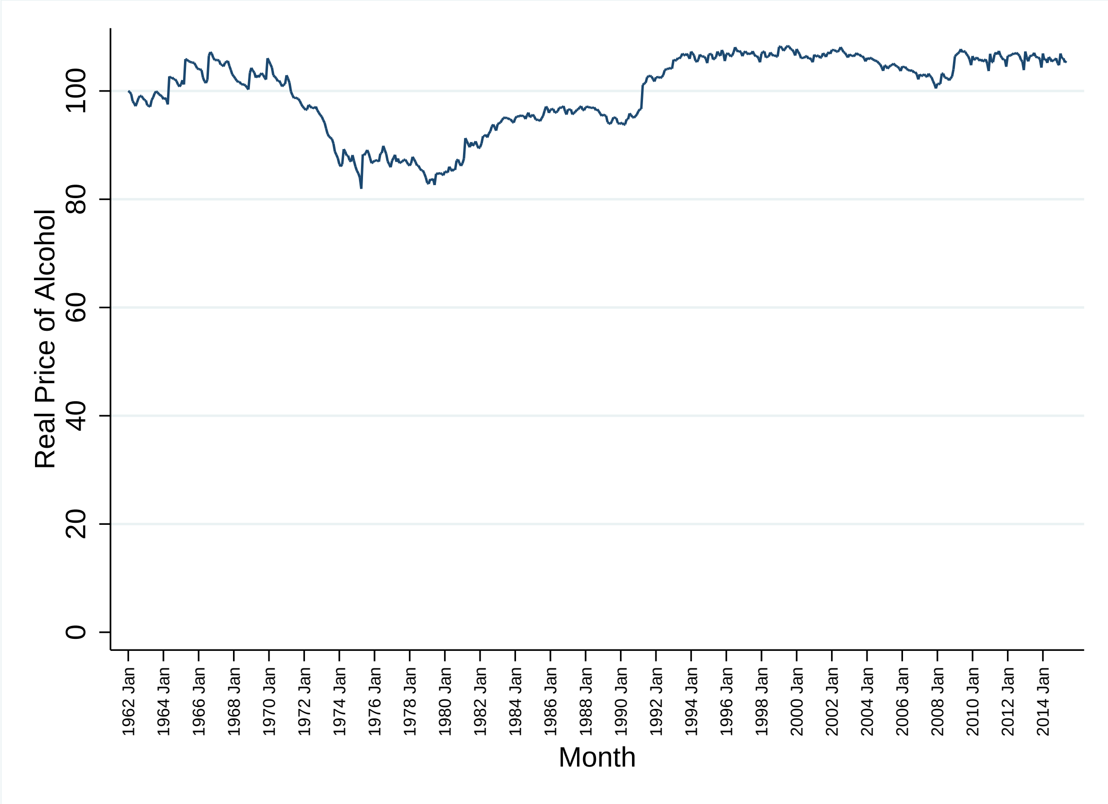
4.1 Introduction

This chapter examines drinking over the lifecycle, using repeated cross-sectional data to form synthetic cohorts. The purpose of this piece of work is to look at how alcohol consumption changes with age, and over separate birth cohorts. This work is an extension of existing work and its contribution is to advance understanding of these changes over the drinking distribution, rather than simply looking at the mean consumption of cohorts. This is particularly important because, as already mentioned throughout this thesis, it is the heaviest drinkers who are of most concern because the social costs of alcohol are non-linear and it is the heaviest drinkers who cause the greatest harms. Modelling and predicting *heavy* drinking, as opposed to drinking in itself, is therefore useful for policymakers and health researchers. A particularly heavy drinking cohort, for example, will have implications for health resources in the future as the cohort ages.

This chapter also extends the work on alcohol consumption over the lifecourse by, for the first time, including price as an explanatory factor in the age-period-cohort analysis. Figure 4.1 shows how the real price of alcohol (converted to real prices by using the

ONS RPI All Items Long Run Series) has changed over time.

Figure 4.1: Long Term Real Price of Alcohol



This chapter begins by adapting methods already used in the literature to examine changes across the drinking distribution. It then looks at whether price plays a role in determining consumption in two ways: firstly looking at the long-run price elasticity across cohorts, and secondly whether the price of alcohol when the cohort begins drinking (assumed to be when they are 18) affects the cohort's alcohol consumption. It then uses pseudo-panel methods, where pseudo-panel membership is defined by birth cohort and sex, to test for rational addiction in the data.

The results of this chapter show that alcohol consumption has been steadily rising across birth cohorts, such that the younger generations are drinking more than their preceding older generations were at their age. Women in particular are drinking more over successive birth cohorts. There is no substantive evidence that this has been affected by long-run price, as measured by the long-run retail price index for alcohol. Although evidence is found to support the theory of rational addiction, in that previous and future consumption are predictors of current consumption, the parameter for price is insignificant.

4.2 Literature Review

4.2.1 Drinking and the Life Course

4.2.1.1 Kemm (2003)

Kemm (2003) presented findings from work on age and cohort trends in alcohol consumption using the General Household Survey from 1980 to 1998. He notes that the question used in the General Household Survey changed the method of recording the amount of alcohol consumed in 1986. Prior to 1986, the General Household Survey asked three questions to determine typical alcohol consumption. Firstly, it asked whether the respondent drank at all. Those who had drunk in the last year were asked about consumption of five types of drink (shandy, beer, spirits, fortified wine, and wine). To measure consumption, it first asked the respondents how often they consumed each beverage, and then asked them how much they had drunk 'on any one occasion in the last 12 months'. The product of these two scores (frequency and quantity) allowed the author to calculate the estimated weekly consumption of each respondent. Since 1986, respondents have simply been asked their average weekly alcohol consumption. This is often provided by drink type and quantity, and converted into alcohol units by the survey administrators.

The problem with the questioning method prior to 1986 is that the product of frequency and quantity is prone to large measurement error. The optional responses for frequency are: most days; 3-4 days per week; 1-2 per week; 1-2 per month; 1-2 per 6 months; 1-2 per year; not at all. If measurement error happens here, it is multiplied by the amount of drink consumed (which is a continuous variable), which can have a large effect. It is expected that this measurement error might occur more in infrequent drinkers, because their typical consumption may be harder to define.

Kemm (2003) first analyses the proportion of 'non- or very light drinkers' by age and 5-year birth cohort. This group has mean weekly consumption below 1 unit of alcohol. He finds that 'non- or very light drinking' increases with respect to age, but that there is very little difference across cohorts, especially amongst men - although the oldest birth cohorts of men appear to have much higher rates of low drinking compared to their slightly younger counterparts. That is, he finds that men born between 1912 and 1916 are more likely to be a 'non- or very light drinker' than men born between 1917 and 1921. Females appear to have more pronounced differences between cohorts, and there is a clear age effect with older respondents more likely to be a 'non- or very light drinker', even within the same cohort. This age effect appears to be less strong amongst the younger birth cohorts. The second analysis is on the proportion of 'heavy drinkers': males drinking more than 21 units per week, and women drinking more than14 units per week[1]. He finds that the proportion drinking heavily falls with age, as might be expected, although there is again very little difference across birth cohorts amongst males. For females, each successive birth cohort appears to have a higher proportion of heavy drinkers.

There are a few notable limitations to Kemm's study. Firstly, it is only the *proportions* of the population who fall into each of the defined drinking groups, which is interesting but does not show how consumption has changed within the heavy drinkers. Even if the proportion of heavy drinkers has increased from 10% to 20% across birth cohorts, it is not necessarily clear whether consumption amongst these heavy drinkers has increased. Secondly, price does not feature, which may explain some differences across cohorts, who face different prices at the same age. It could be that a cultural shift has occurred, or it could simply be the case that prices are lower in the later years. Finally, no confidence intervals are fitted around the proportions, meaning it is impossible to tell whether the

[1]Note that these were the previous maximum recommended weekly consumption.

shifts in consumption across ages and birth cohorts is statistically significant or simply due to sample error.

4.2.1.2 Meng et al (2014b)

Meng et al (2014) use the same dataset to model age, period and cohort (APC) effects. Survey respondents are assigned a 5-year birth cohort, a 5-year observation period (ie. the year the wave of the General Household Survey took place), and a 5-year age band. The variables are grouped to avoid the problem of a mechanical relationship between age, period and birth year,

$$Period = BirthYear + Age \tag{4.1}$$

which would result in perfect collinearity in the three variables and lead to one being dropped. The study also controls for household income, education, ethnicity, and country. It is potentially more interesting to see how different birth cohorts, made up of different ethnicities and educational levels, have different drinking patterns, although using these control variables does eliminate any mitigating factor - for example since alcohol is a normal good if younger cohorts have higher incomes, then they would be expected to consume more which would be detected as a cohort effect. The flipside is that the *conditional* consumption may not be as interesting to policymakers, because it is the level of alcohol consumption in the population that is of importance. The study uses a negative binomial regression, despite the dependent variable not being discrete, and the justification this is not given. The negative binomial regression is explicitly for modelling count variables, and its advantage over the Poisson regression is that it allows for over-dispersion[2]. However it is useful that alcohol consumption, rather than the proportion of heavy drinkers as in Kemm (2003), is used as the dependent variable, since this gives the reader more information about the level of drinking. As discussed above, it is interesting to see whether the proportion of heavy drinkers has increased across

[2]The Poisson distribution has only one free parameter, setting a fixed relationship between the mean and the variance

birth cohorts, but also whether consumption within heavy drinkers has also increased.

The results paint a very similar story to Kemm (2003), chiefly that abstention rates are increasing over age and period for both men and women whilst consumption increases over successive birth cohorts. The shape of the odds ratio for abstention across birth cohorts is u-shaped for both men and women, which was not found in Kemm's analysis.

Again, the same limitation stands as in Kemm (2003) - that the effects are only shown at the mean for each age band, period, and birth cohort. However, there is also a problem with the use of age-period-cohort analysis in that the issue of collinearity between the three has not been satisfactorily resolved. There is still a mechanical relationship between age, period and cohort as shown in Equation 4.1, and although non-overlapping groups solves the problem from a statistical viewpoint in that a separate effect can be estimated, its true effect cannot be identified. The grouping essentially creates noise around the mechanical relationship. It may also be the case that the control variables create enough variation for the model to be fitted. A review, and criticism, of the methods used to overcome the identification problem is provided by Bell and Jones (2013). They argue that "no model is able to solve the identification problem because the identification problem is inherent to the real-world processes being modelled". Bell and Jones (2013) also argue that 'solving' the problem by grouping the data is explicitly assuming that consumption is fixed within that group. For example, there is no difference between in consumption *ceteris paribus* for two people in 1996 and 1998.

4.2.2 Rational Addiction

The theory of rational addiction, as set out by Becker and Murphy (1988), posits that an individual decides present consumption as a function of both past consumption and future consumption. Therefore, how much someone drinks at the start of their drinking 'lifetime' (ie. when they turn 18 in the United Kingdom) might have an effect on later drinking. Policy may be effective by reducing consumption in the early stages of the drinking ‘lifetime’.

The theory of rational addiction has been empirically tested the expected effects on previous and future prices have been found. This is true for alcohol (eg. Waters and Sloan, 1995; Bentzen et al, 1999; Baltagi and Griffin, 2002) and tobacco (eg. Chaloupka and Wechsler, 1997; Escario and Molina, 2001), as well as other goods including coffee (Olekalns and Bardsley, 1996) and cocaine (Grossman and Chaloupka, 1998).

However, the theory of rational addiction is not supported by empirical work by Skog and Melberg (2006), who test the theory using the demand for distilled spirits in Denmark during and after the first world war, where the prices were increased through rationing. The authors state that this can be thought of as a natural experiment, but there may be questions of whether alcohol consumption increased post-war was not related to price but rather other reasons such as trauma. There is also no control group for the study, which means that distinguishing this is difficult.

Another criticism is that the empirical method for testing rational addiction is not valid. Auld and Grootendorst (2004) use the empirical method to test for rational addiction to seemingly non-addictive goods such as milk, eggs and orange juice. They find that the empirical test for rational addiction is especially flawed when using time series data, and when the data exhibits serial correlation.

4.3 Data and Methods

4.3.1 Data

Ideally, a long panel survey would be able to answer with certainty the change in alcohol consumption across birth cohorts and age. Sadly such data does not exist; instead cross-sectional surveys using different participates in each wave are routinely collected. One such survey is the General Household Survey, which has been conducted on an annual basis since 1971. Alcohol data, in any comparable form, has only been collected since 1986. The data used in this chapter runs from 1986 until 2010, although data on alcohol consumption is not collected annually. The waves used in this chapter are 1986, 1988, 1990, 1992, 1994, 1996, 1998, 2000, 2001, 2002, 2005, 2006, 2008 and 2010. Given the change in question in 1986 around alcohol consumption, previous waves are not used as the consistency of the data may introduce bias - the change in question may pick up a false period effect, and this bias could effect other parameters too.

The General Household Survey is a multi-purpose survey, collecting information on a range of topics. The data is collected through face-to-face interviews, carried out on roughly 12,000 households per year. The survey asks detailed questions surrounding alcohol; for each drink, the respondent is asked quantity-frequency questions. From this, the estimated weekly units are calculated, which is the dependent variable used in this chapter.

The survey collects data on all members of the household, but for the purposes of this study only those aged between 18 and 90 are kept. For the age-period-cohort analysis using price, only those aged between 18 and 69 are used because the price of alcohol when the respondent was 18 is only known for these ages.

4.3.2 Methods

The methods used here are similar to work using pseudo-panels, such as the work described in the previous chapter by Meng et al (2014a). As Deaton (1985) states, a pseudo-panel cell need not be a birth cohort but could be any segment of the population whose properties do not change over time, whereas synthetic cohorts explicitly require birth cohorts to form the panel cells. The use of synthetic cohorts to monitor changes both across the lifecycle and across birth cohorts is well established in the literature having been used to study social phobia and discrimination (Thomas et al, 1994; Heimberg et al, 2000), and female labour force participation (Contreras et al, 2005).

Pseudo-panel work, and work using synthetic cohorts, usually collapse each cohort to get a mean value of the dependent variable, or estimate a parameter based on the mean marginal effect. Whilst this is often informative, it does not provide the whole story. Collapsing each cohort by quantiles of the distribution can reveal more subtle effects which may be missed by convential analysis at the mean. For example, Chevalier et al (2004) go on to analyse the effect of raising the school leaving age at different quantiles. They find no difference in effect across the earnings distribution, which is particularly interesting for the bottom of the earnings distribution.

For this study, each respondent in the 14 waves of the GHS is assigned a 5-year birth cohort, listed in Table 4.1. It is obvious that there is a potential small sample problem for early cohorts, and in fact the earliest birth cohort only features in one wave of data so is dropped from the analysis. Each wave of the GHS is collated into five-year time periods, and 5-year age bands are constructed as defined in Table 4.2.

Table 4.1: Birth Cohort Definitions

Birth Cohort	**Min**	**Max**	**Observations**
1	1901	1905	872
2	1906	1910	2538
3	1911	1915	4755
4	1916	1920	6752
5	1921	1925	10791
6	1926	1930	12070
7	1931	1935	13404
8	1936	1940	14735
9	1941	1945	16709
10	1946	1950	19994
11	1951	1955	18142
12	1956	1960	19186
13	1961	1965	20532
14	1966	1970	18498
15	1971	1975	12538
16	1976	1980	7695
17	1981	1985	5010
18	1986	1990	2567

Table 4.2: Age Band Definitions

Age Band	Min Age	Max Age	Observations
1	18	20	8079
2	21	25	15311
3	26	30	17740
4	31	35	18994
5	36	40	19695
6	41	45	19305
7	46	50	17873
8	51	55	16493
9	56	60	16152
10	61	65	15676
11	66	70	14070
12	71	75	11836
13	76	80	9072
14	81	85	5337
15	86	90	1185

This chapter uses three methods to examine trends in alcohol consumption over the lifecourse. The first is to extend Kemm's analysis by collapsing the data by quantile - lower quartile, median, upper quartile, and the 90th percentile - for each birth cohort and gender separately. Kemm's analysis of non-drinkers, and heavy drinkers (those drinking over 14 and 21 units per week for women and men respectively), is also updated using the more recent data. The results are presented both graphically and in table form, using a simple regression

$$U_{cgtq} = \alpha + \beta_{cgq}\text{Age}_{cgtq} + \varepsilon_{cgtq} \tag{4.2}$$

where U is weekly units of alcohol, and the subscripts refer to birth cohort c, gender g, time t and quantile q. Notice that this allows the coefficient on age to differ by birth cohort, gender and quantile.

The second analysis is a quantile extension of the work done by Meng et al (2014b), which regresses units against age, period and cohort. This is identified in the same manner as Meng et al (2014b), by using age bins which are smaller or larger than the period and cohort bins, and by having them overlap. It does not use the control variables used in Meng et al (2014b), instead preferring to see how alcohol consumption has changed unconditional on other variables. The equation used is

$$U_{cgtq} = \alpha + \beta_1 \text{AgeBand}_{cgtq} + \beta_2 \text{TimePeriod}_t + \beta_3 \text{BirthCohort}_{cgq} + \varepsilon_{cgtq} \tag{4.3}$$

An alternative to imposing restrictions on the bins is by modelling a cohort effect using a variable which varies by cohort but does not have the 'adding-up' problem that age-period-cohort modelling suffers from. In this work, the price at the start of a cohort's drinking 'lifetime' (when they turn 18) takes the place of the cohort effect. That is, any cohort effect arises because of price differences at the age of 18. Figure 4.1 shows that the real-terms price of all alcohol (as measured by the Office for National Statistics) has remained fairly constantsince 1962, save for a period between 1970 and 1980 when it was almost 20% cheaper than the long-run average.

The theory of rational addiction is tested empirically by collapsing each birth cohort and sex 'cell' into quantiles, using the equation as in Auld and Grootendorst (2004)

$$c_{i,t,q} = \theta_1 c_{i,t-1,q} + \theta_2 c_{i,t+1,q} + \theta_3 p_t + u_{i,t,q} \tag{4.4}$$

where i refers to the birth cohort and sex cell, t is year, and q is the quantile of interest.

4.3.2.1 Possible Methodological Limitations

There are two methodological limitations in using synthetic cohort quantiles. The first is that respondents may die over time, and that these are more likely to be the heavier drinking respondents. However, this is also true of the usual synthetic cohort which estimates differences at the mean. Whilst impossible to adjust for in this study, it is worth remembering when interpreting the results. If heavier drinkers are more likely to die prematurely, then the older waves of cohorts are likely to feature fewer heavy drinkers and this will bias the estimated consumption of this cohort downwards. Secondly, respondents may change their consumption over time, causing switching to take place within cohorts across time. For example, a heavy drinking youth who features in the top consumption decile may decrease consumption which brings them into the median of the cohort. Whilst this is unlikely, it is more likely that the heaviest drinkers quit drinking altogether. However, this criticism could be levelled at synthetic analysis using cohort means: the mean need not be representative of a single member of the cohort.

4.4 Results

4.4.1 Quantile Extension of Kemm (2003)

Figure 4.2 to Figure 4.13 show how each quantile of the drinking distribution (including abstention) has changed over birth cohort and age. This is simply an extension of Kemm (2003), which used almost exactly the same method. The same overall picture appears, with younger birth cohorts tending to drink more than the preceding cohort at the same age. For example, looking at the median males (Figure 4.8) at the age of 60, it is clear that the cohort born 1936-40 (shown in red) is drinking roughly 2.5 units less than the younger cohort born 1941-45 (shown in blue).

However, the results depart from Kemm (2003) in finding that the youngest cohorts are beginning to drink less than their older peers. The benefit of the quantile analysis is that it is obvious that this is mostly true in the lower quartile of the male drinking distribution as shown in **??**. Taking just the youngest three birth cohorts - shown in red, orange, and yellow respectively - the youngest birth cohort are drinking approximately 4 units per week compared to 7 for the preceding cohorts. However, this is not true for women, where it appears that consumption is increasing across successive birth cohorts. It also seems that the female heavy drinkers (the 90th percentile, as shown in **??**) are not decreasing their consumption as much as they age across successive birth cohorts. The shape of the fitted values suggests that women in each cohort are not reducing their consumption at the same rate that men of the same birth cohort are. Again taking the

1936-40 birth cohort at 60, shown in red, men are decreasing their consumption as they age whereas women are not, and may even be increasing their consumption.

Figure 4.2: Abstention - Male

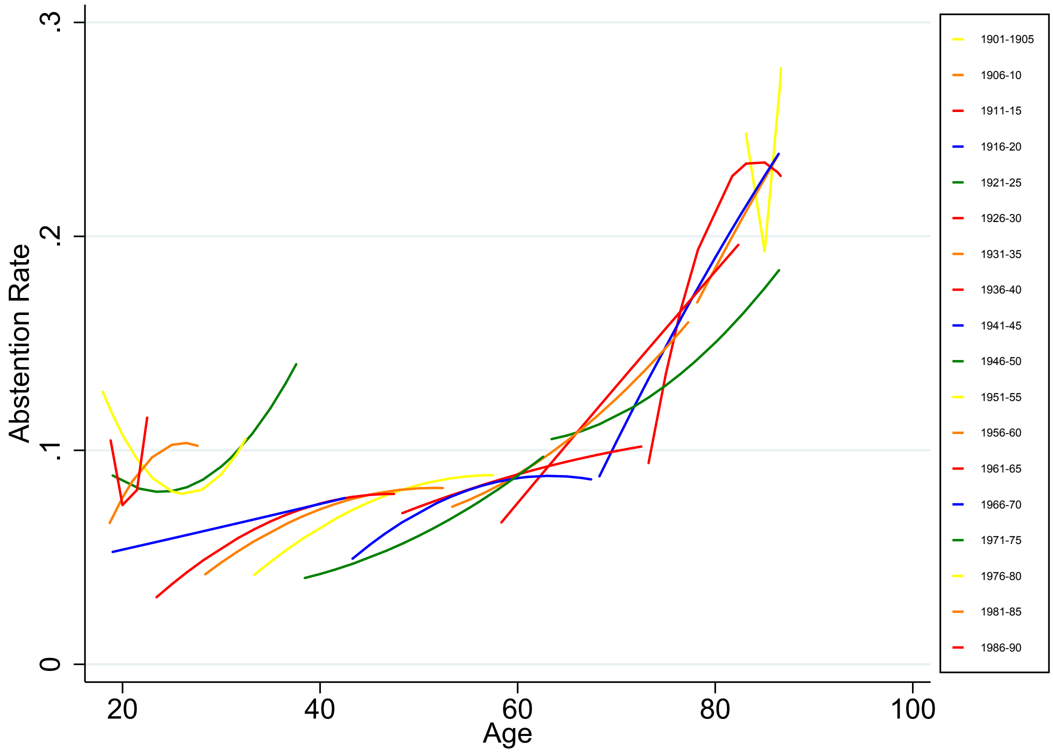


Figure 4.3: Abstention - Female

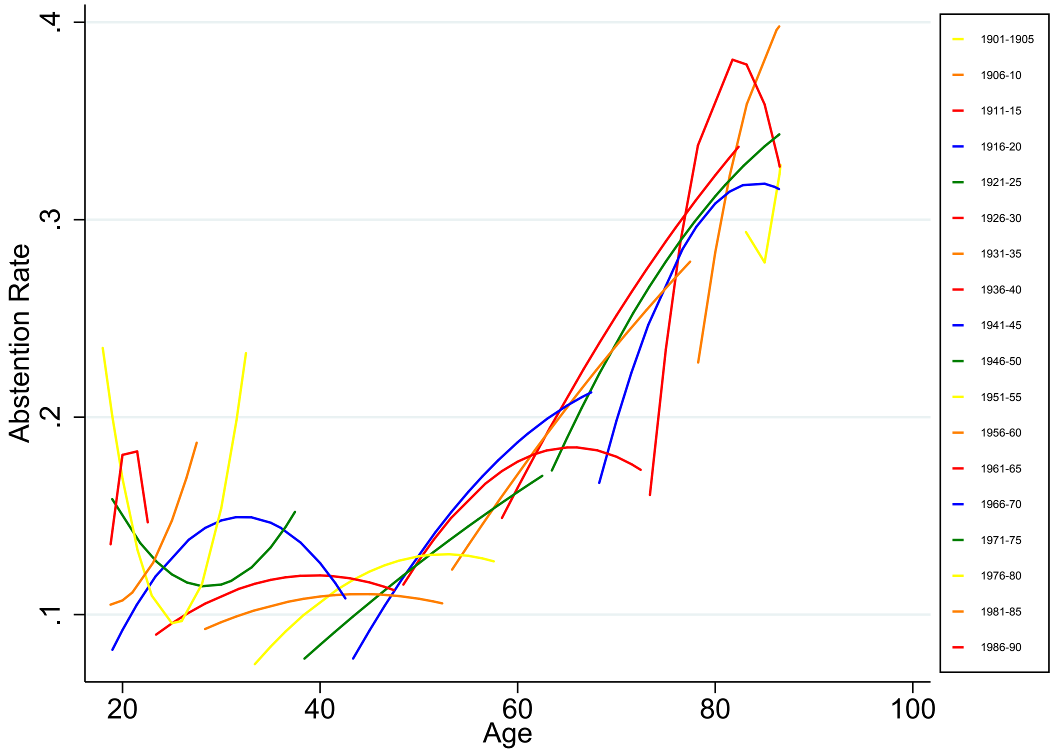


Figure 4.4: Over Guidelines (Kemm's 'Heavy Drinkers') - Male

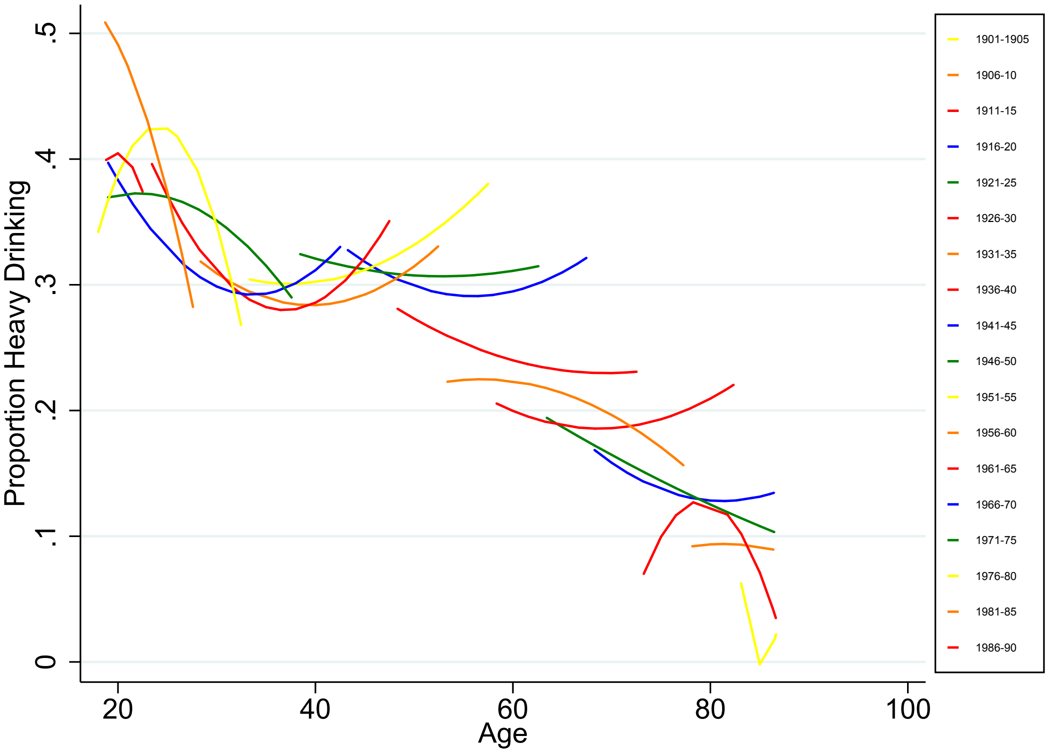


Figure 4.5: Over Guidelines (Kemm's 'Heavy Drinkers') - Female

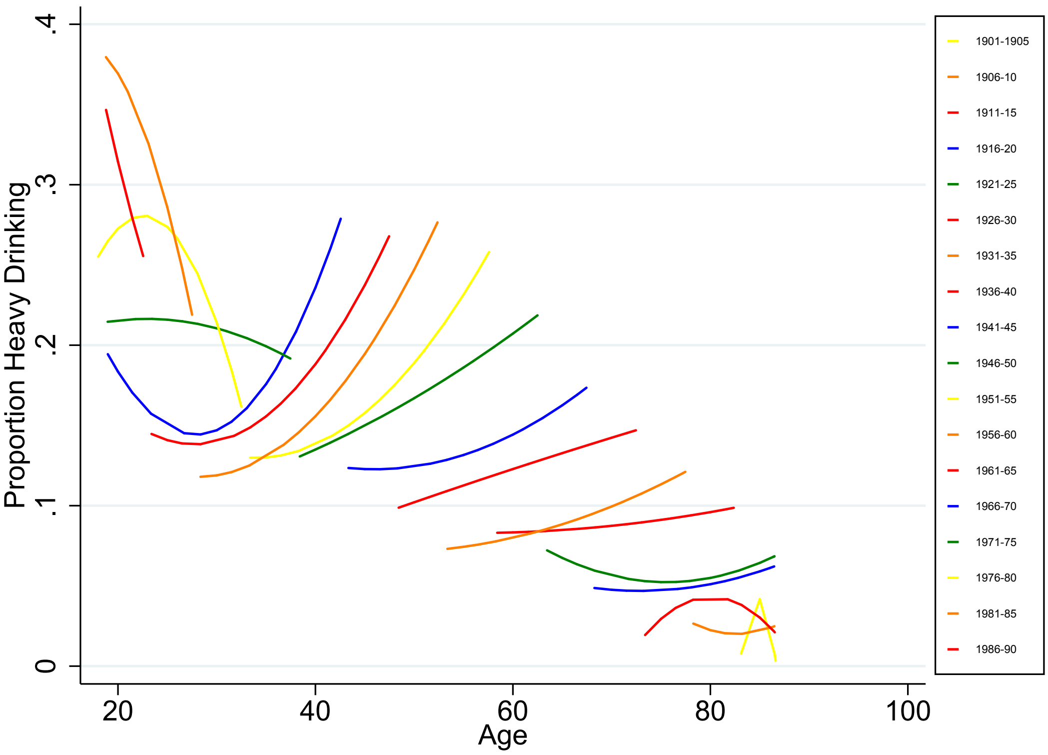


Figure 4.6: Lower Quartile - Male

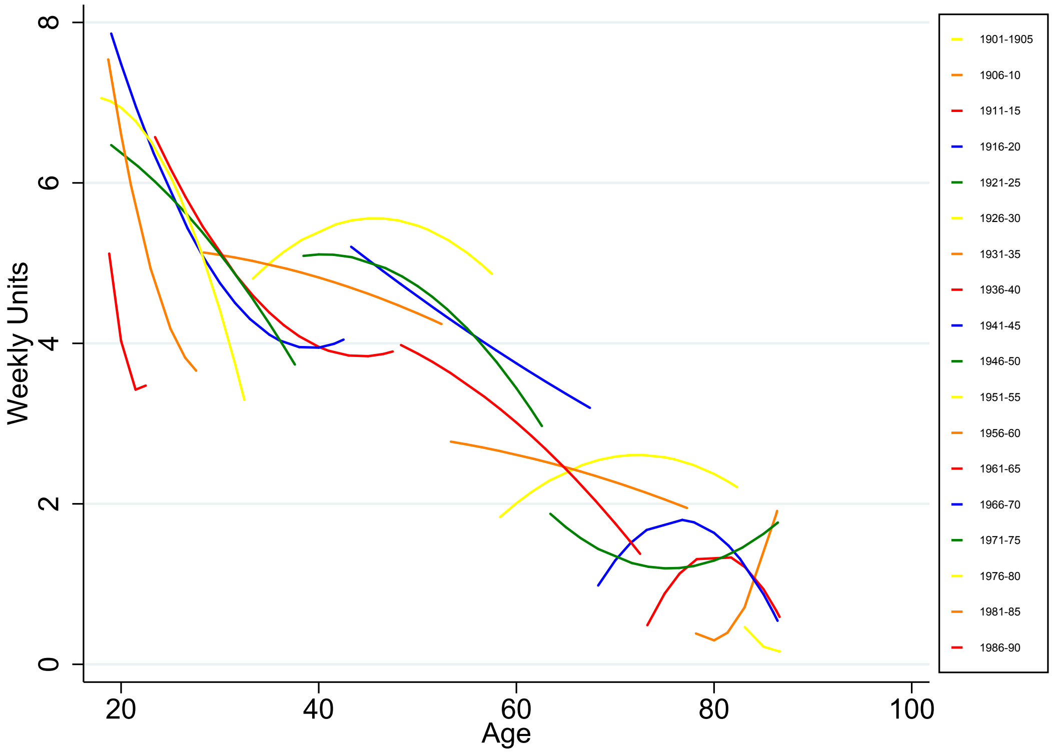


Figure 4.7: Lower Quartile - Female

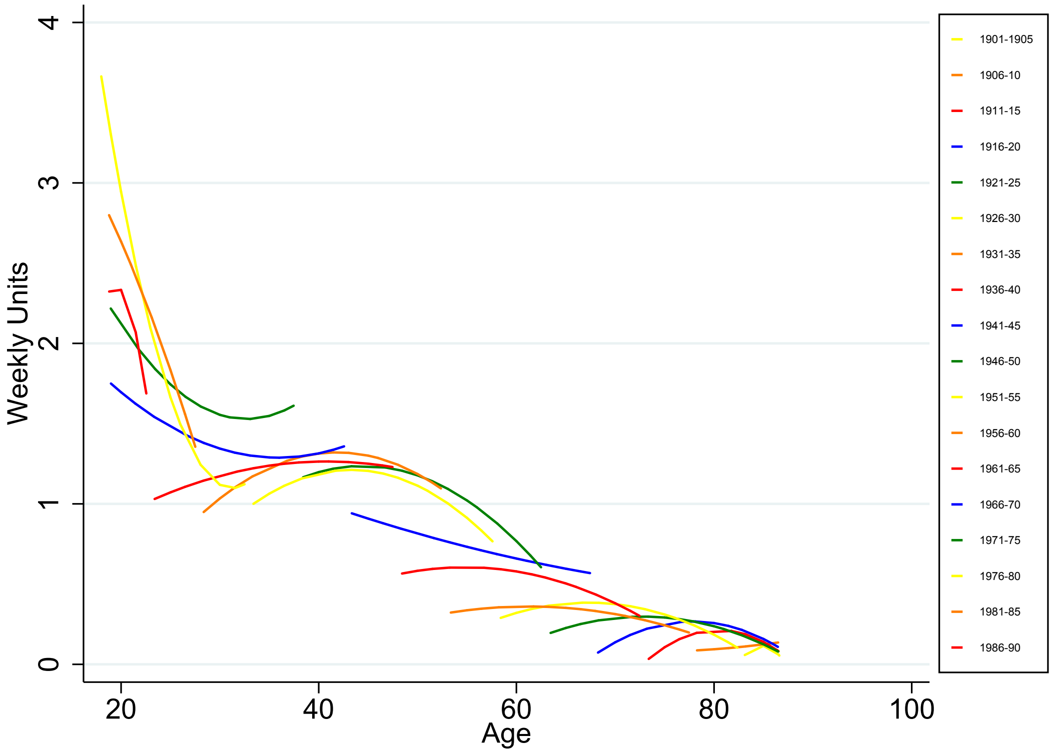


Figure 4.8: Median - Male

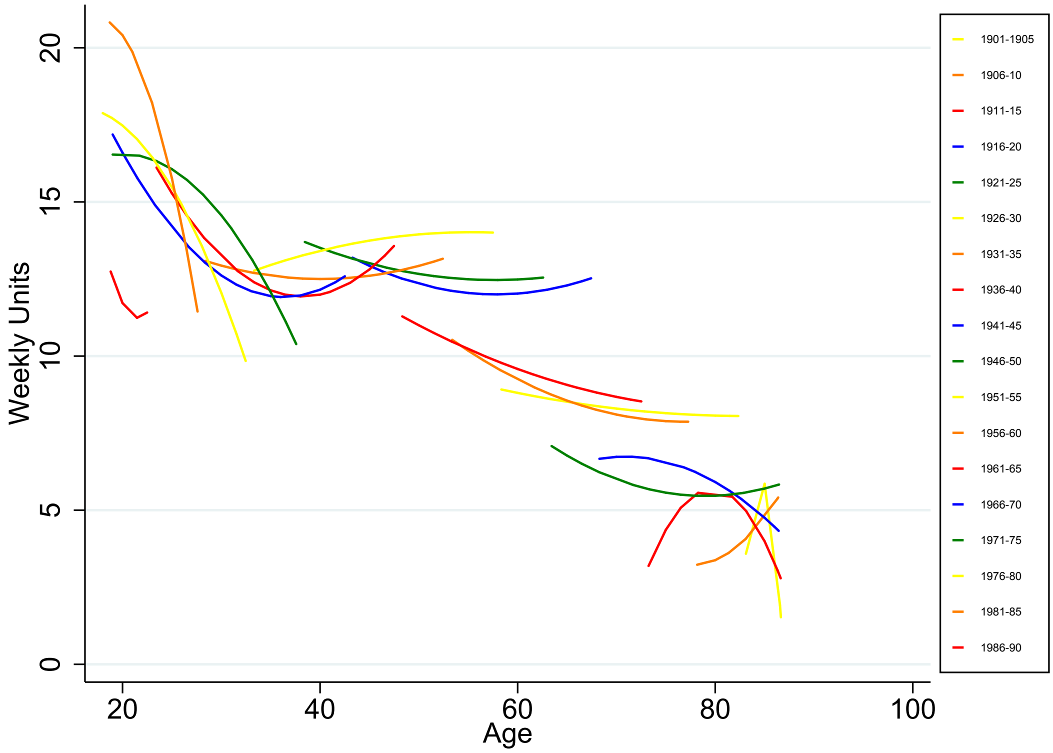


Figure 4.9: Median - Female

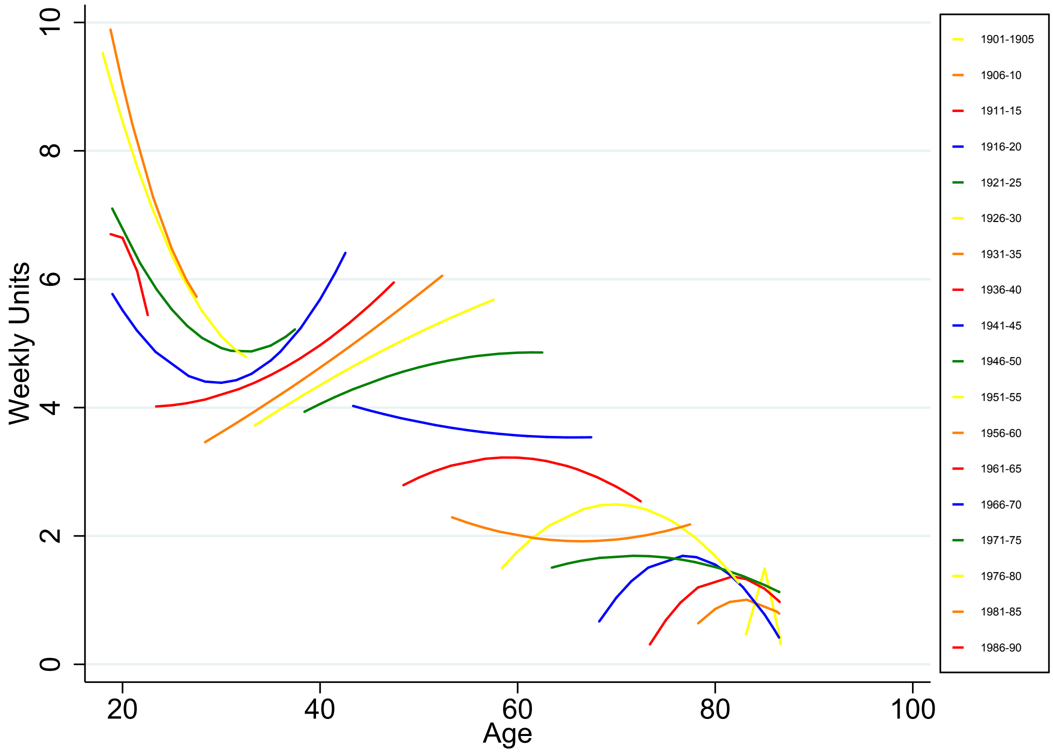


Figure 4.10: Upper Quartile - Male

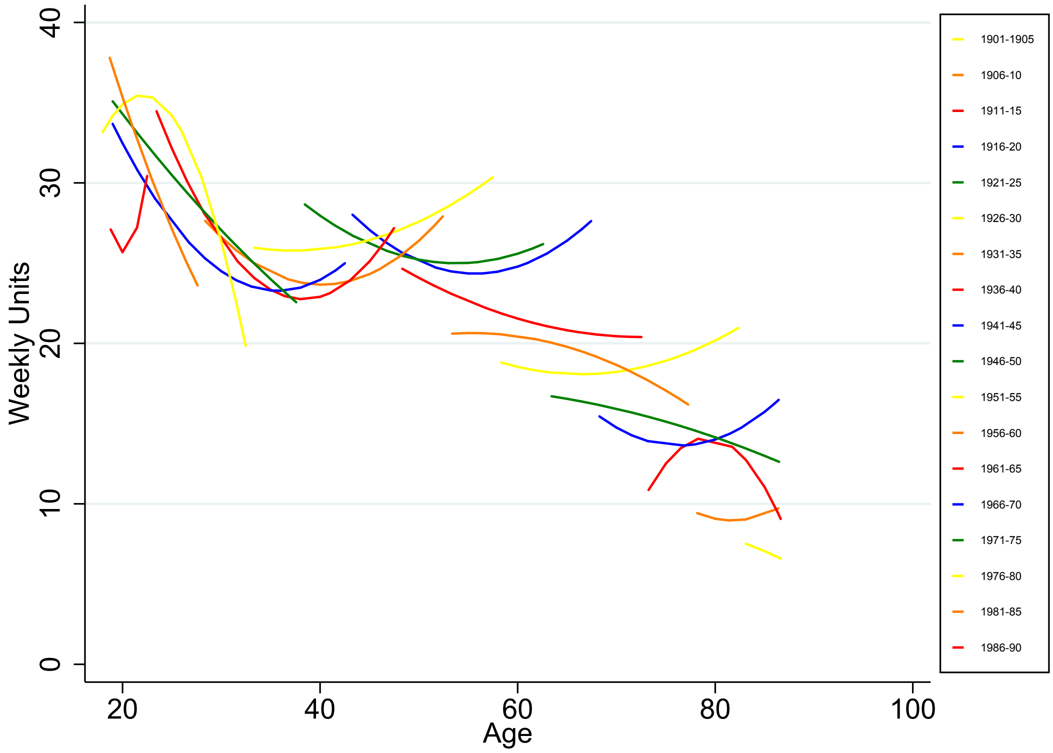


Figure 4.11: Upper Quartile - Female

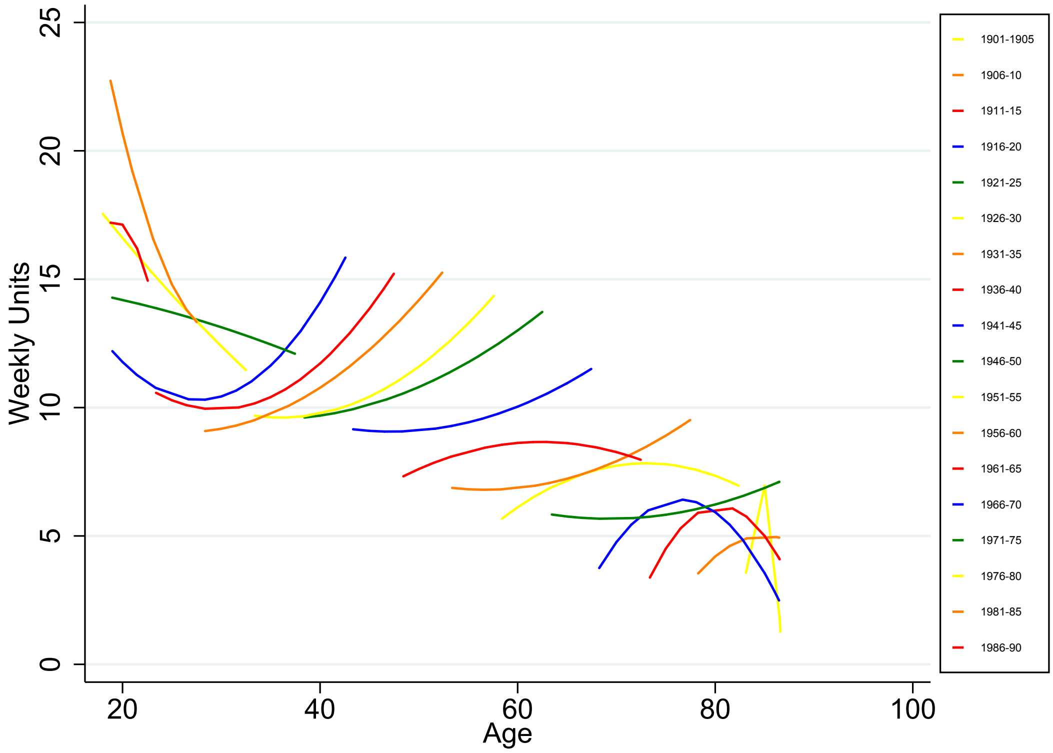


Figure 4.12: 90th Percentile - Male

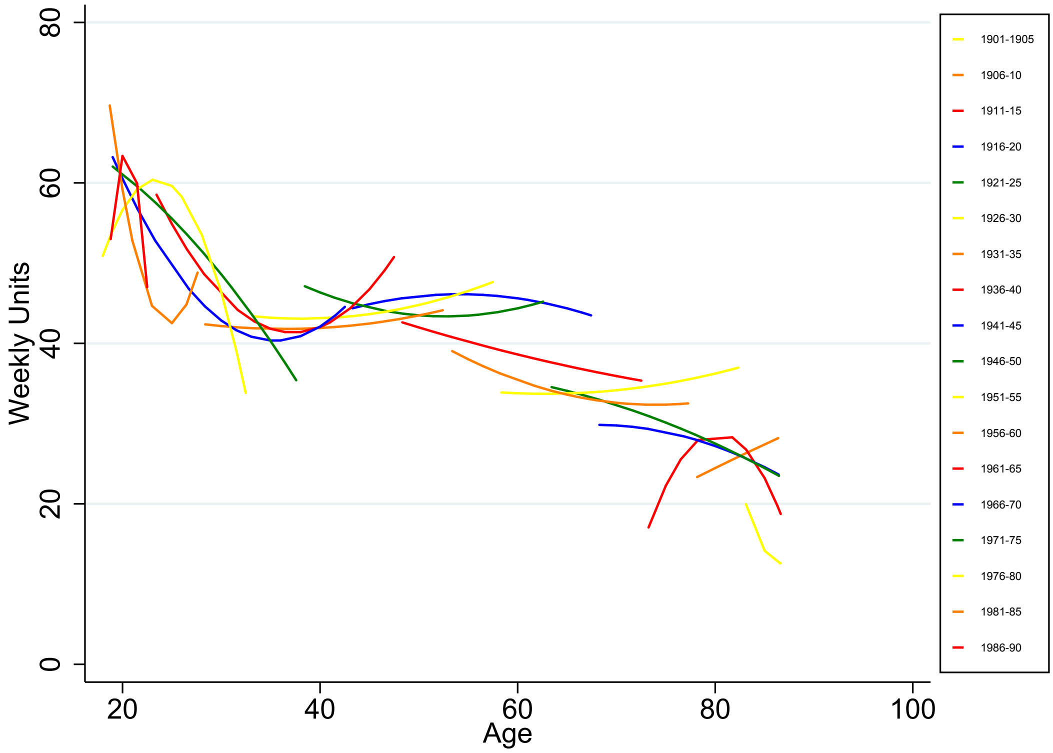
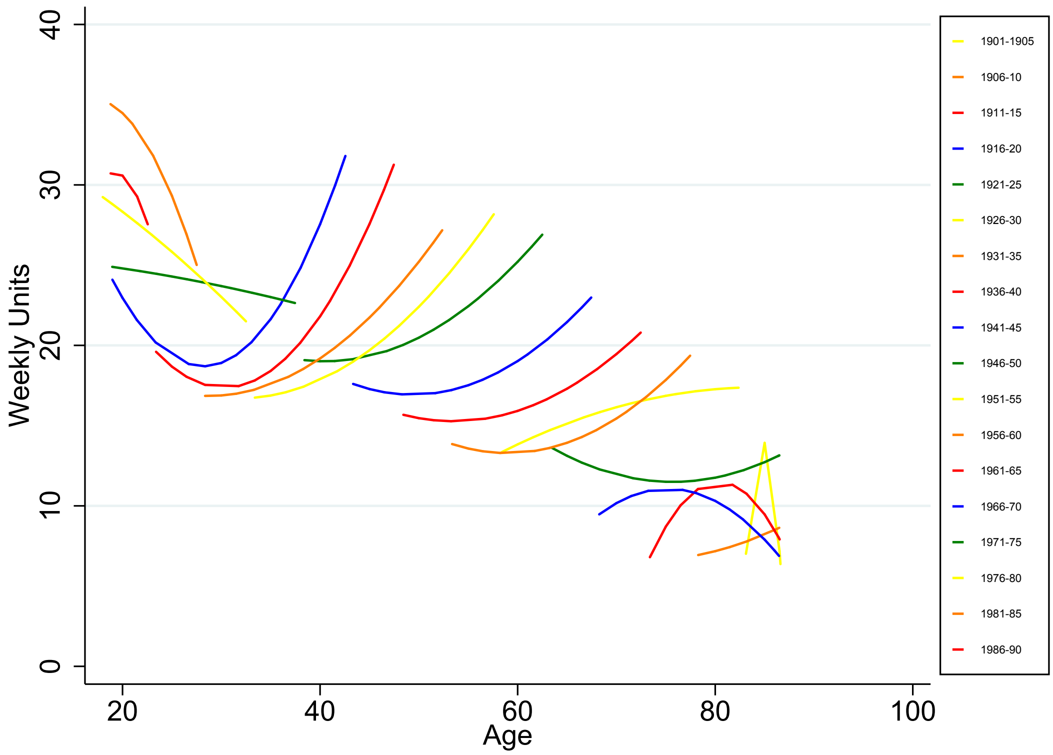


Figure 4.13: 90th Percentile - Female



4.4.2 Quantile Extension of Meng et al (2014b)

Figure 4.14 to Figure 4.21 show the quantile results from age-period-cohort modelling as done by Meng et al (2014b). These are first shown in table form in Table 4.3 to Table 4.11. Age effects are not significant for males, but are for females, meaning that (*ceteris paribus*) older women drink more than younger women. This is found across all quantiles of the drinking distribution. There appears to have been a downward trend in consumption for both genders and all quantiles across time period. This means that, holding all else constant, every type of drinker has decreased their consumption. Finally, birth cohort appears to have the strongest trend, in that every birth cohort appears to have consumed more than their older counterpart did at the same age. There appears to be a slight decrease for the youngest male cohorts, although this is not statistically significant.

However, the results highlight the limitation of age-period-cohort analysis. The results from the quantile extension of Kemm (2003) show that alcohol consumption decreases with age. However, the age-period-cohort results suggest that older women consume more alcohol than younger women. This only arises because the model acts as if it is ageing people without changing birth cohort *and* period. This is clearly impossible, and the reason for Bell and Jones' (2013) criticisms of the method.

Table 4.3: Negative Binomial Results - Age Coefficients

	Male	Female
Age 18-20	1.024	0.605***
	(0.0647)	(0.0417)
Age 21-25	1.055	0.605***
	(0.0583)	(0.0364)
Age 26-30	0.902**	0.537***
	(0.0426)	(0.0276)
Age 31-35	0.834***	0.582***
	(0.0328)	(0.0249)
Age 36-40	0.881***	0.701***
	(0.0279)	(0.0243)
Age 41-45	0.900***	0.839***
	(0.0227)	(0.0233)
Age 46-50	0.985	0.930***
	(0.0201)	(0.0210)
Age 56-60	0.997	1.069***
	(0.0209)	(0.0250)
Age 61-65	1.031	1.216***
	(0.0271)	(0.0353)
Age 66-70	1.067*	1.317***
	(0.0356)	(0.0487)
Age 71-75	0.972	1.396***
	(0.0401)	(0.0637)
Age 76-80	0.962	1.474***
	(0.0486)	(0.0814)
Age 81-85	1.005	1.767***
	(0.0618)	(0.119)
Age 86-90	0.970	1.425***
	(0.0856)	(0.131)

Exponentiated coefficients; Standard errors in parentheses. Observations: 85,423 (male); 92,070 (female)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4: Negative Binomial Results - Period Coefficients

	Male	Female
Period 1985-1989	1.064***	1.099***
	(0.0230)	(0.0258)
Period 1990-1994	1.083***	1.107***
	(0.0166)	(0.0185)
Period 2000-2004	1.005	0.992
	(0.0160)	(0.0171)
Period 2005-2009	0.927***	0.873***
	(0.0189)	(0.0196)
Period 2010-2014	0.942**	0.913***
	(0.0272)	(0.0287)

Exponentiated coefficients; Standard errors in parentheses. Observations: 85,423 (male); 92,070 (female)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.5: Negative Binomial Results - Cohort Coefficients

	Male	Female
Born 1901-1905	0.314***	0.179***
	(0.0342)	(0.0188)
Born 1906-1910	0.404***	0.233***
	(0.0309)	(0.0187)
Born 1911-1915	0.475***	0.305***
	(0.0293)	(0.0204)
Born 1916-1920	0.544***	0.347***
	(0.0277)	(0.0195)
Born 1921-1925	0.583***	0.436***
	(0.0241)	(0.0201)
Born 1926-1930	0.692***	0.530***
	(0.0232)	(0.0201)
Born 1931-1935	0.736***	0.636***
	(0.0197)	(0.0192)
Born 1936-1940	0.851***	0.792***
	(0.0180)	(0.0192)
Born 1946-1950	1.048**	1.214***
	(0.0206)	(0.0267)
Born 1951-1955	1.134***	1.380***
	(0.0287)	(0.0383)
Born 1956-1960	1.096***	1.569***
	(0.0348)	(0.0543)
Born 1961-1965	1.155***	1.780***
	(0.0452)	(0.0757)
Born 1966-1970	1.112**	2.044***
	(0.0519)	(0.103)
Born 1971-1975	1.207***	2.351***
	(0.0666)	(0.141)
Born 1976-1980	1.334***	2.922***
	(0.0865)	(0.206)
Born 1981-1985	1.251***	3.130***
	(0.0930)	(0.251)
Born 1986-1990	1.212**	3.471***
	(0.105)	(0.324)

Exponentiated coefficients; Standard errors in parentheses. Observations: 85,423 (male); 92,070 (female)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.6: Quantile Regression - Male - Age

	Q25	Q50	Q75	Q90
Age 18-20	0.0356	0.102	0.0771	0.121*
	(0.166)	(0.0902)	(0.0824)	(0.0722)
Age 21-25	0.0933	0.151*	0.135*	0.142**
	(0.145)	(0.0786)	(0.0718)	(0.0629)
Age 26-30	-0.0617	0.00885	-0.0346	-0.0667
	(0.124)	(0.0672)	(0.0614)	(0.0538)
Age 31-35	-0.196*	-0.109*	-0.128**	-0.103**
	(0.103)	(0.0560)	(0.0511)	(0.0448)
Age 36-40	-0.115	-0.0904**	-0.109***	-0.0849**
	(0.0836)	(0.0453)	(0.0414)	(0.0363)
Age 41-45	-0.140**	-0.0400	-0.0812**	-0.0674**
	(0.0662)	(0.0359)	(0.0328)	(0.0287)
Age 46-50	-0.0209	-0.0269	-0.0211	-0.0143
	(0.0537)	(0.0291)	(0.0266)	(0.0233)
Age 56-60	-0.130**	-0.00798	-0.0306	0
	(0.0546)	(0.0296)	(0.0270)	(0.0237)
Age 61-65	-0.134*	-0.0374	0.00624	0.0337
	(0.0683)	(0.0370)	(0.0338)	(0.0296)
Age 66-70	-0.0301	-0.00778	0.0457	0.0219
	(0.0870)	(0.0472)	(0.0431)	(0.0378)
Age 71-75	-0.310***	-0.133**	-0.0965*	-0.0553
	(0.108)	(0.0584)	(0.0533)	(0.0467)
Age 76-80	-0.263**	-0.125*	-0.124*	-0.0604
	(0.132)	(0.0715)	(0.0653)	(0.0572)
Age 81-85	-0.129	-0.0287	-0.0785	0.00154
	(0.160)	(0.0869)	(0.0793)	(0.0695)
Age 86-90	-0.0952	-0.0786	-0.117	-0.259***
	(0.229)	(0.124)	(0.113)	(0.0993)

Standard errors in parentheses. Observations: 85,423

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7: Quantile Regression - Male - Period

	Q25	Q50	Q75	Q90
Period 1985-1989	0.0854	0.00947	0.0475*	0.0369
	(0.0568)	(0.0308)	(0.0281)	(0.0246)
Period 1990-1994	0.180***	0.0541**	0.0513***	0.0559***
	(0.0401)	(0.0217)	(0.0199)	(0.0174)
Period 2000-2004	-0.0293	0.00928	0.00880	-0.00364
	(0.0416)	(0.0225)	(0.0206)	(0.0180)
Period 2005-2009	-0.166***	-0.0873***	-0.0702***	-0.0566**
	(0.0533)	(0.0289)	(0.0264)	(0.0231)
Period 2010-2014	-0.196***	-0.0379	-0.0130	-0.0374
	(0.0758)	(0.0411)	(0.0375)	(0.0329)

Standard errors in parentheses. Observations: 85,423

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.8: Quantile Regression - Male - Cohort

	Q25	Q50	Q75	Q90
Born 1901-1905	-2.398***	-1.270***	-1.239***	-0.945***
	(0.280)	(0.152)	(0.139)	(0.121)
Born 1906-1910	-2.136***	-1.280***	-0.972***	-0.679***
	(0.199)	(0.108)	(0.0983)	(0.0862)
Born 1911-1915	-1.396***	-0.805***	-0.637***	-0.590***
	(0.161)	(0.0872)	(0.0796)	(0.0698)
Born 1916-1920	-1.057***	-0.652***	-0.538***	-0.436***
	(0.133)	(0.0721)	(0.0658)	(0.0577)
Born 1921-1925	-0.954***	-0.615***	-0.463***	-0.385***
	(0.108)	(0.0586)	(0.0535)	(0.0469)
Born 1926-1930	-0.548***	-0.372***	-0.320***	-0.275***
	(0.0875)	(0.0474)	(0.0433)	(0.0380)
Born 1931-1935	-0.451***	-0.324***	-0.280***	-0.251***
	(0.0698)	(0.0378)	(0.0345)	(0.0303)
Born 1936-1940	-0.228***	-0.191***	-0.166***	-0.0907***
	(0.0553)	(0.0300)	(0.0274)	(0.0240)
Born 1946-1950	0.149***	0.0576**	0.0282	0.0233
	(0.0515)	(0.0279)	(0.0255)	(0.0223)
Born 1951-1955	0.293***	0.133***	0.103***	0.0633**
	(0.0663)	(0.0360)	(0.0328)	(0.0288)
Born 1956-1960	0.260***	0.0786*	0.0188	0.0408
	(0.0835)	(0.0453)	(0.0413)	(0.0362)
Born 1961-1965	0.266***	0.0898	0.0650	0.0907**
	(0.103)	(0.0557)	(0.0508)	(0.0446)
Born 1966-1970	0.290**	0.0754	0.0286	0.0555
	(0.123)	(0.0664)	(0.0606)	(0.0532)
Born 1971-1975	0.291**	0.0814	0.0838	0.125**
	(0.145)	(0.0785)	(0.0717)	(0.0629)
Born 1976-1980	0.400**	0.159*	0.164*	0.161**
	(0.170)	(0.0922)	(0.0842)	(0.0738)
Born 1981-1985	0.428**	0.121	0.0648	0.132
	(0.196)	(0.106)	(0.0969)	(0.0849)
Born 1986-1990	0.200	-0.0319	0.0772	0.124
	(0.227)	(0.123)	(0.112)	(0.0985)

Standard errors in parentheses. Observations: 85,423

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.9: Quantile Regression - Female - Age

	Q25	Q50	Q75	Q90
Age 18-20	-0.977***	-0.711***	-0.418***	-0.432***
	(0.204)	(0.134)	(0.0918)	(0.0883)
Age 21-25	-0.940***	-0.731***	-0.460***	-0.423***
	(0.177)	(0.116)	(0.0800)	(0.0769)
Age 26-30	-0.976***	-0.827***	-0.562***	-0.540***
	(0.151)	(0.0995)	(0.0683)	(0.0657)
Age 31-35	-0.777***	-0.713***	-0.495***	-0.449***
	(0.126)	(0.0828)	(0.0569)	(0.0547)
Age 36-40	-0.430***	-0.476***	-0.321***	-0.310***
	(0.102)	(0.0670)	(0.0460)	(0.0443)
Age 41-45	-0.202**	-0.218***	-0.169***	-0.144***
	(0.0815)	(0.0535)	(0.0368)	(0.0354)
Age 46-50	0.00896	-0.0293	-0.0623**	-0.0427
	(0.0661)	(0.0434)	(0.0298)	(0.0287)
Age 56-60	0.0856	0.0349	0.0822***	0.0929***
	(0.0684)	(0.0449)	(0.0309)	(0.0297)
Age 61-65	0.209**	0.205***	0.173***	0.207***
	(0.0853)	(0.0560)	(0.0385)	(0.0370)
Age 66-70	0.401***	0.259***	0.238***	0.259***
	(0.108)	(0.0711)	(0.0488)	(0.0470)
Age 71-75	0.401***	0.344***	0.283***	0.286***
	(0.134)	(0.0878)	(0.0603)	(0.0580)
Age 76-80	0.432***	0.403***	0.341***	0.344***
	(0.162)	(0.106)	(0.0731)	(0.0703)
Age 81-85	0.720***	0.609***	0.580***	0.512***
	(0.195)	(0.128)	(0.0880)	(0.0846)
Age 86-90	0.720***	0.353**	0.149	0.472***
	(0.264)	(0.173)	(0.119)	(0.114)

Standard errors in parentheses. Observations: 92,070

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.10: Quantile Regression - Female - Period

	Q25	Q50	Q75	Q90
Period 1985-1989	0.318***	0.182***	0.0426	0.0545*
	(0.0690)	(0.0453)	(0.0311)	(0.0299)
Period 1990-1994	0.404***	0.198***	0.0691***	0.0566***
	(0.0493)	(0.0324)	(0.0222)	(0.0214)
Period 2000-2004	-0.0102	0.00543	0.0234	-0.00131
	(0.0504)	(0.0331)	(0.0227)	(0.0218)
Period 2005-2009	-0.390***	-0.241***	-0.132***	-0.0951***
	(0.0650)	(0.0427)	(0.0293)	(0.0282)
Period 2010-2014	-0.575***	-0.239***	-0.0705*	-0.0294
	(0.0925)	(0.0608)	(0.0417)	(0.0401)

Standard errors in parentheses. Observations: 92,070

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.11: Quantile Regression - Female - Cohort

	Q25	Q50	Q75	Q90
Born 1901-1905	-3.482***	-2.768***	-1.595***	-1.462***
	(0.297)	(0.195)	(0.134)	(0.129)
Born 1906-1910	-3.162***	-2.491***	-1.344***	-1.329***
	(0.232)	(0.152)	(0.104)	(0.100)
Born 1911-1915	-2.758***	-1.992***	-1.073***	-1.073***
	(0.194)	(0.128)	(0.0876)	(0.0843)
Born 1916-1920	-2.470***	-1.652***	-0.909***	-0.885***
	(0.164)	(0.107)	(0.0738)	(0.0710)
Born 1921-1925	-2.055***	-1.250***	-0.735***	-0.657***
	(0.134)	(0.0883)	(0.0607)	(0.0583)
Born 1926-1930	-1.349***	-1.009***	-0.562***	-0.500***
	(0.110)	(0.0723)	(0.0497)	(0.0478)
Born 1931-1935	-1.056***	-0.791***	-0.430***	-0.405***
	(0.0876)	(0.0575)	(0.0395)	(0.0380)
Born 1936-1940	-0.588***	-0.305***	-0.251***	-0.228***
	(0.0703)	(0.0461)	(0.0317)	(0.0305)
Born 1946-1950	0.372***	0.275***	0.204***	0.178***
	(0.0643)	(0.0422)	(0.0290)	(0.0279)
Born 1951-1955	0.649***	0.495***	0.331***	0.265***
	(0.0817)	(0.0537)	(0.0369)	(0.0355)
Born 1956-1960	1.002***	0.642***	0.456***	0.365***
	(0.102)	(0.0672)	(0.0462)	(0.0444)
Born 1961-1965	1.212***	0.826***	0.561***	0.460***
	(0.126)	(0.0825)	(0.0567)	(0.0545)
Born 1966-1970	1.505***	0.996***	0.688***	0.618***
	(0.150)	(0.0984)	(0.0676)	(0.0650)
Born 1971-1975	1.795***	1.206***	0.806***	0.714***
	(0.177)	(0.116)	(0.0797)	(0.0766)
Born 1976-1980	2.170***	1.488***	1.004***	0.895***
	(0.208)	(0.136)	(0.0936)	(0.0901)
Born 1981-1985	2.360***	1.549***	1.110***	1.003***
	(0.237)	(0.156)	(0.107)	(0.103)
Born 1986-1990	2.582***	1.631***	1.157***	1.048***
	(0.276)	(0.181)	(0.125)	(0.120)

Standard errors in parentheses. Observations: 92,070

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 4.14: Lower Quartile APC: Male

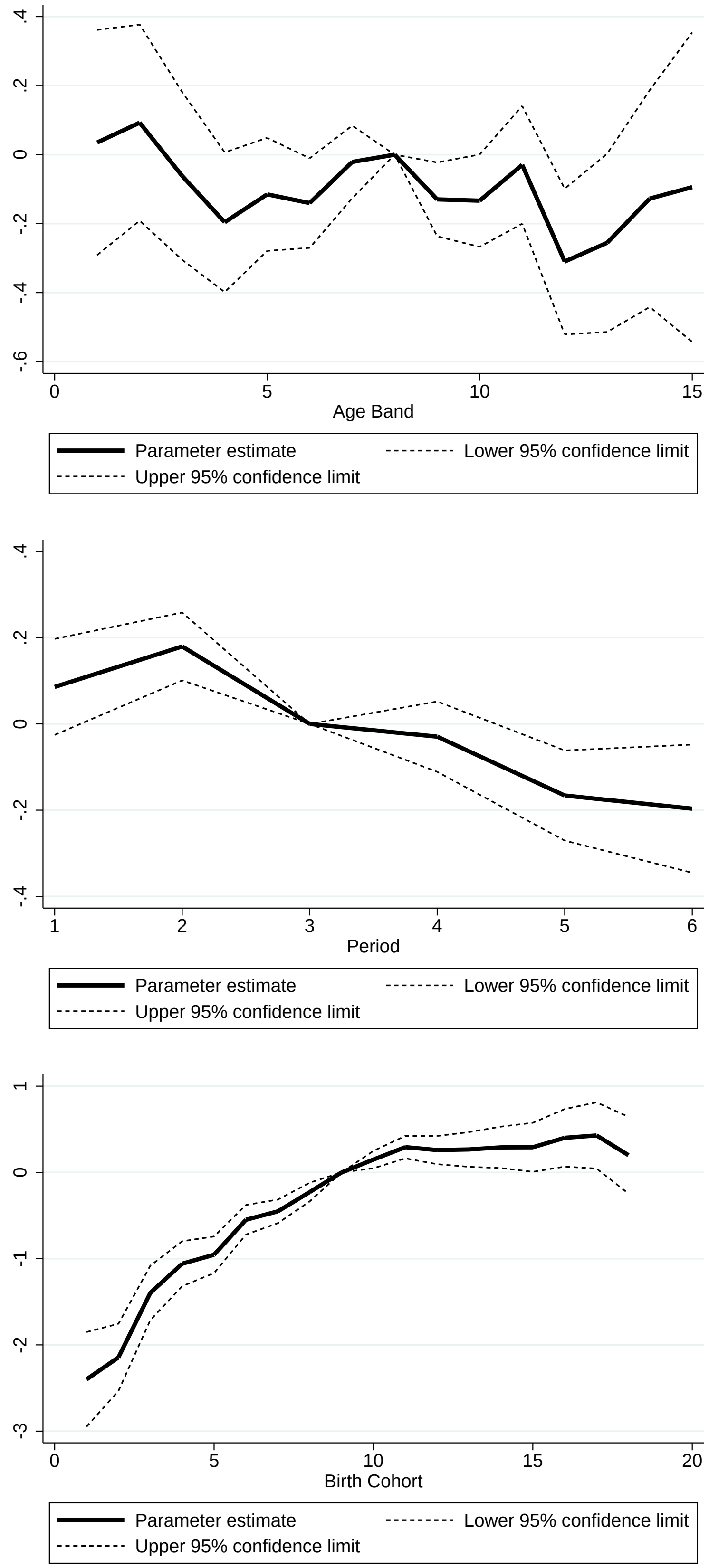


Figure 4.15: Median APC: Male

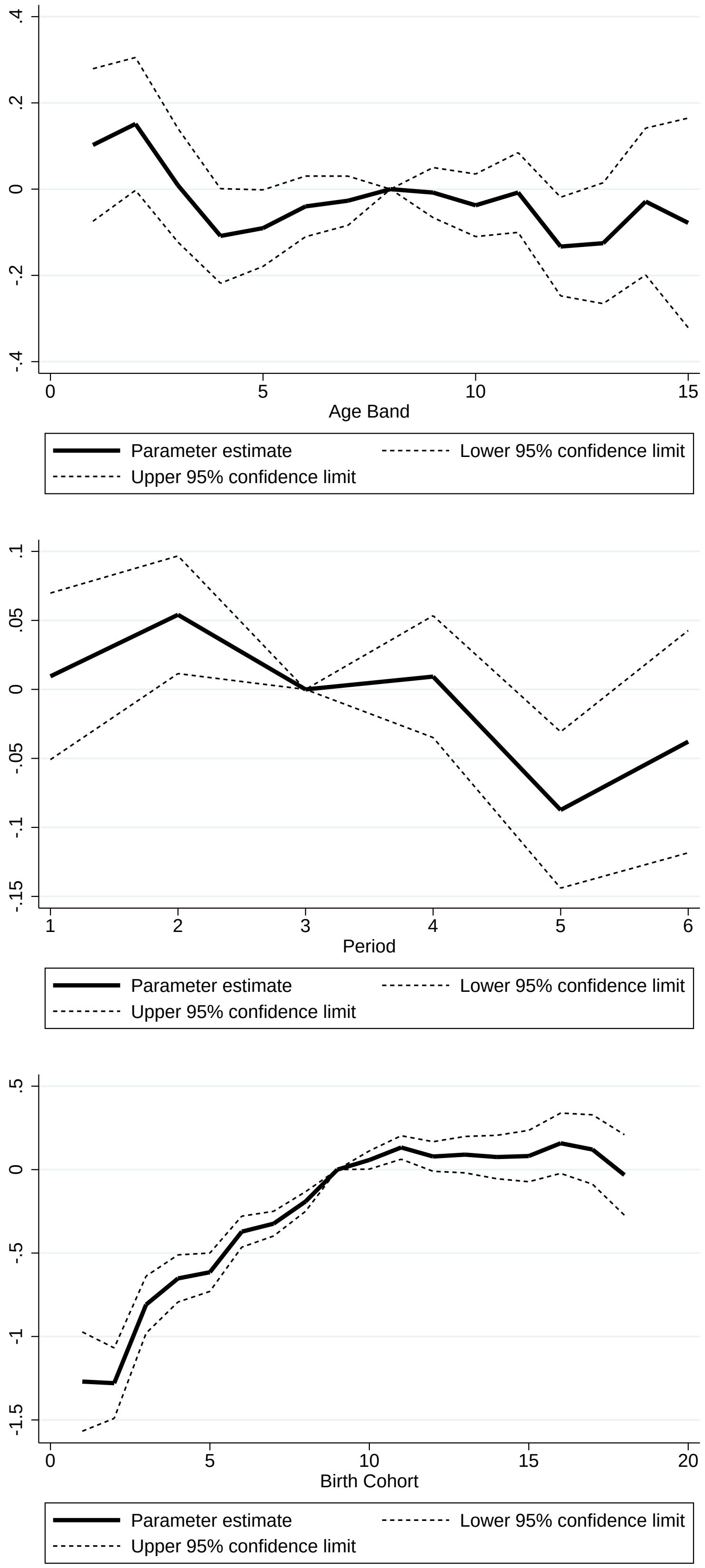


Figure 4.16: Upper Quartile APC: Male

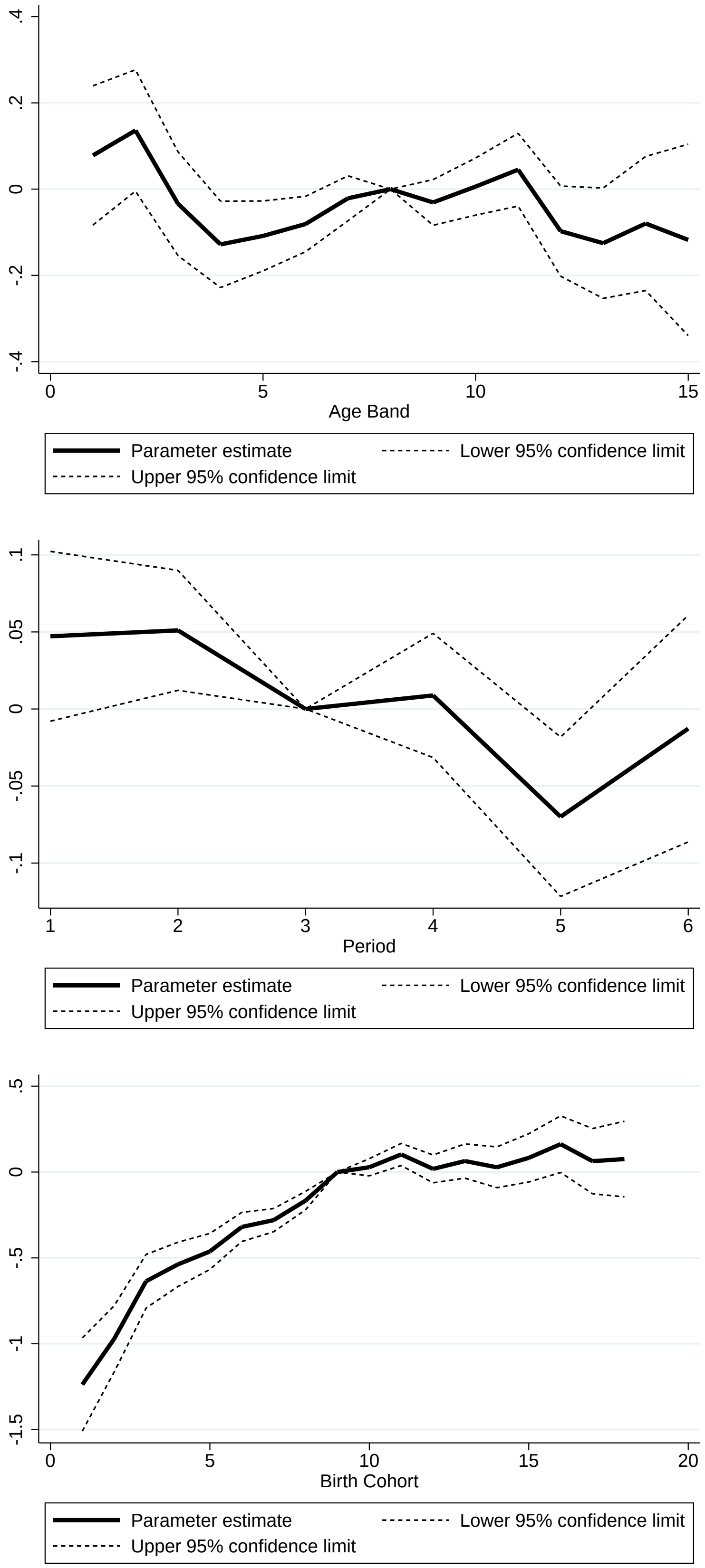


Figure 4.17: 90th Percentile APC: Male

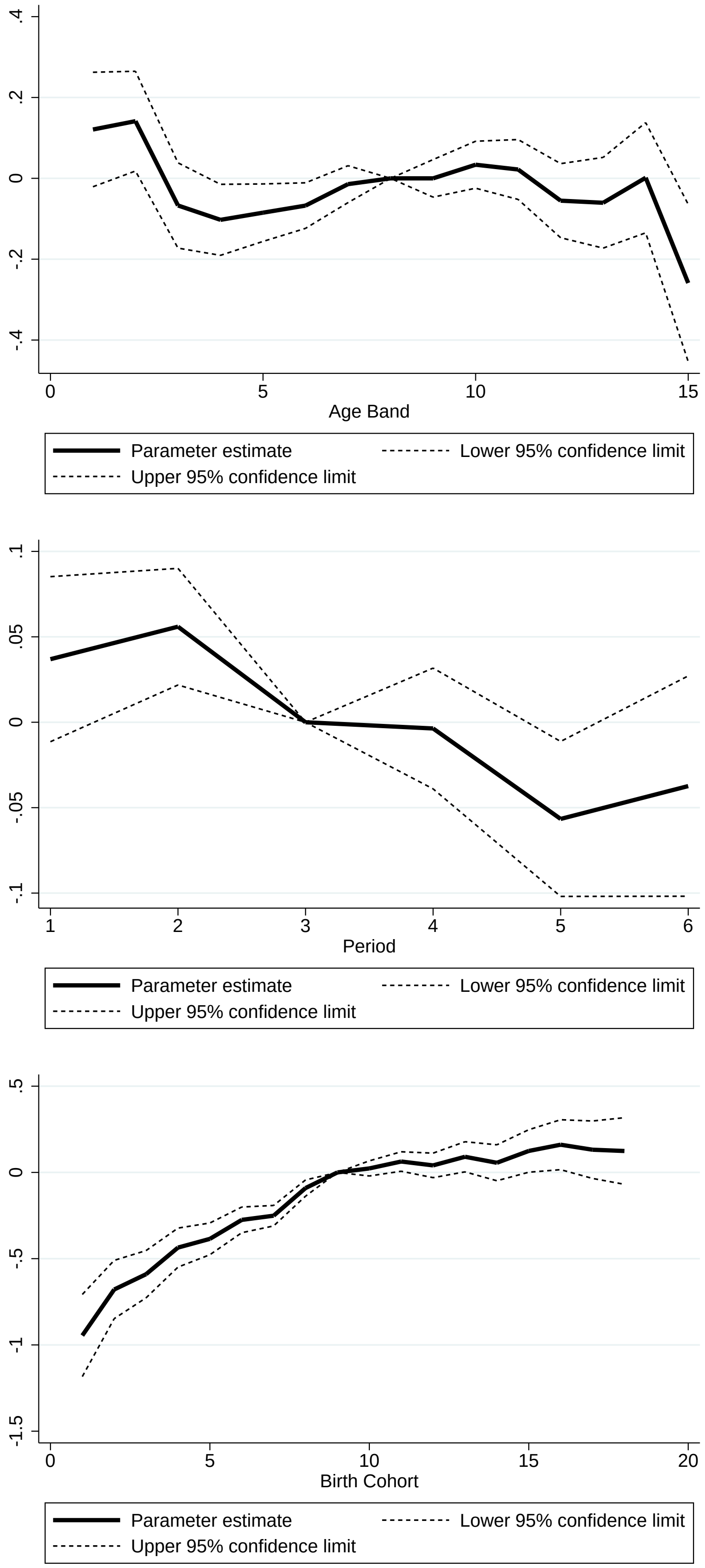


Figure 4.18: Lower Quartile APC: Female

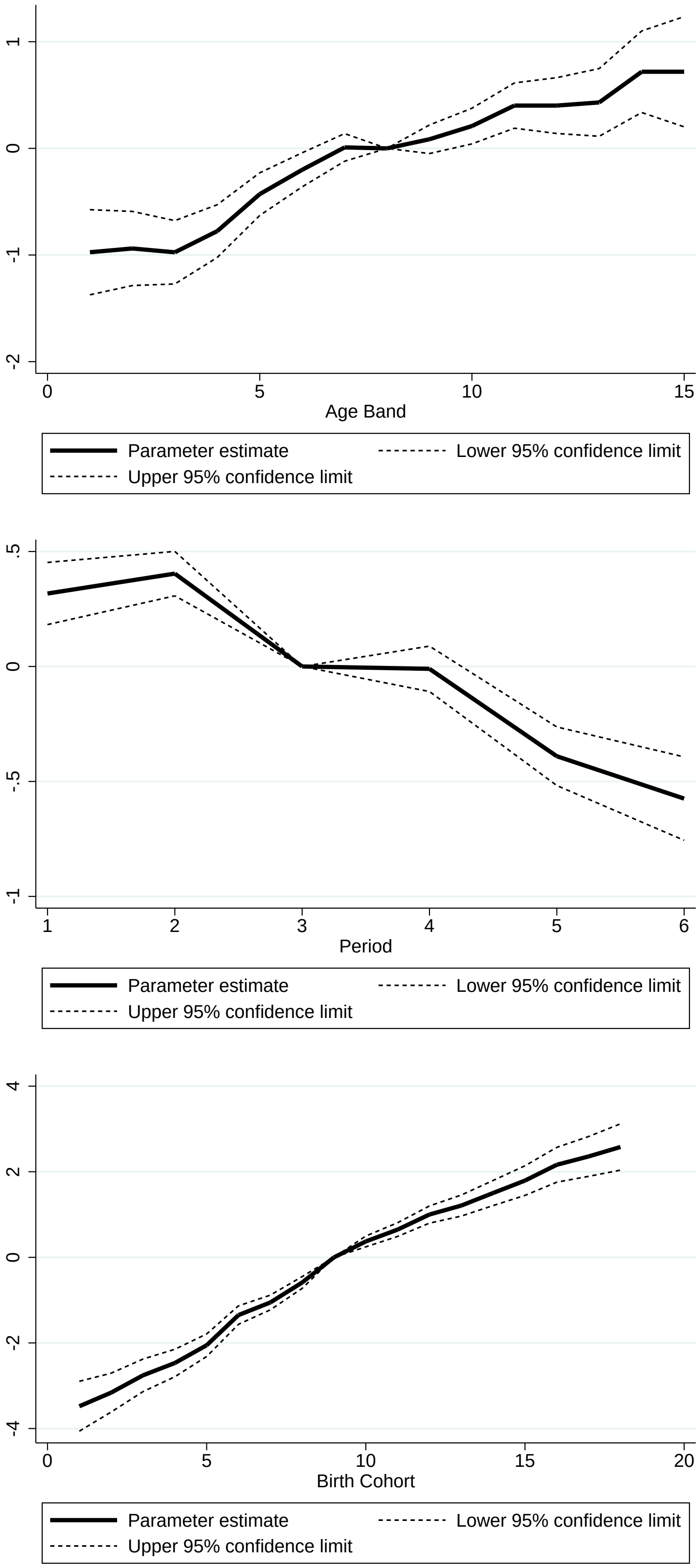


Figure 4.19: Median APC: Female

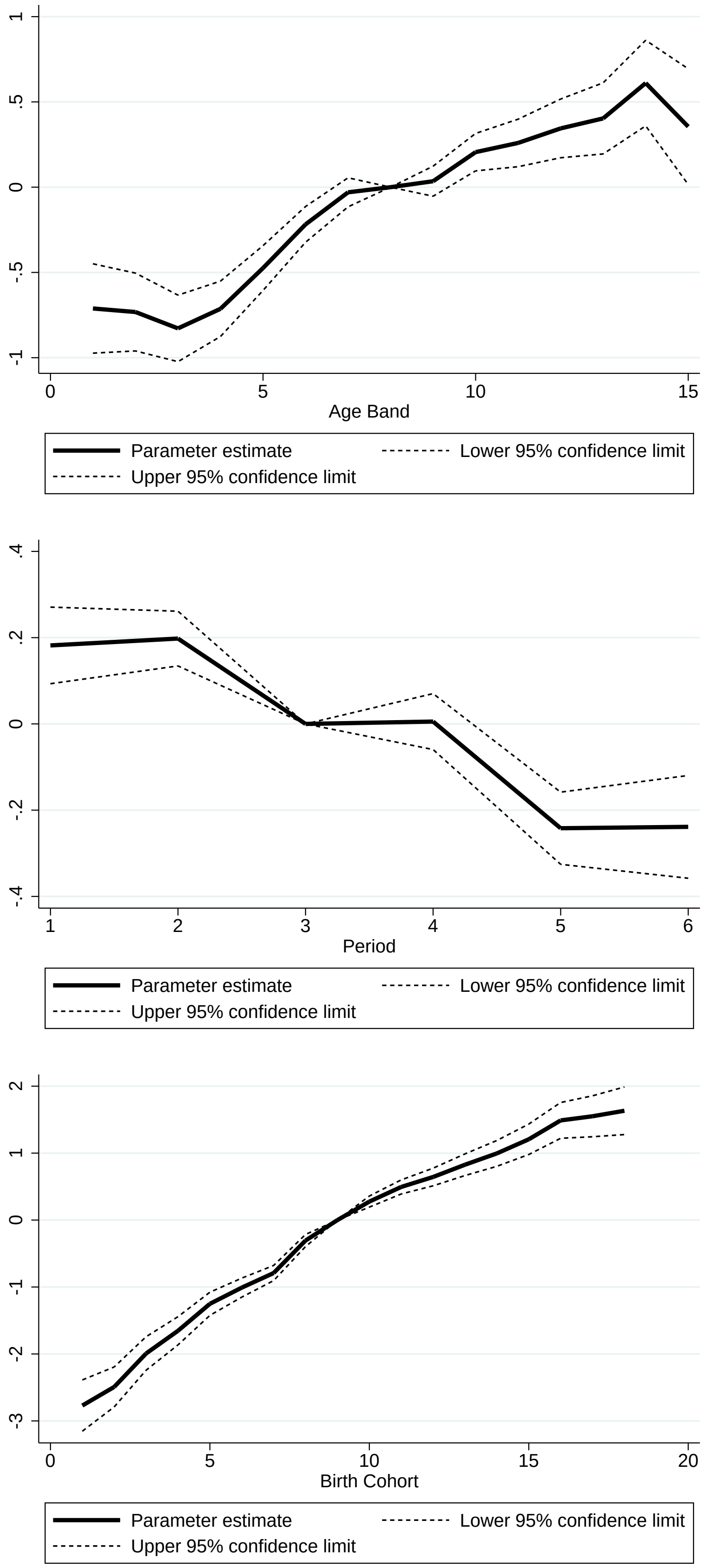


Figure 4.20: Upper Quartile APC: Female

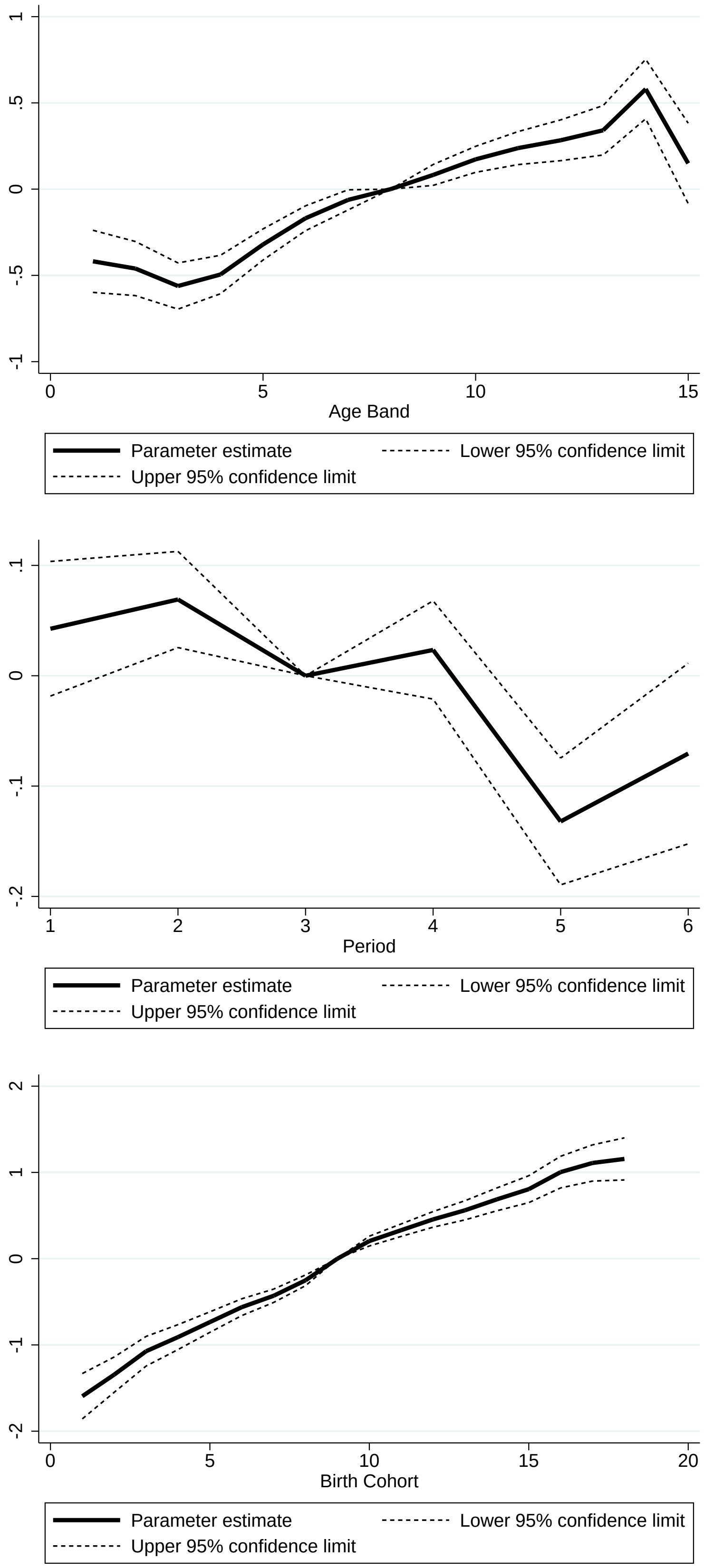


Figure 4.21: 90th Percentile APC: Female

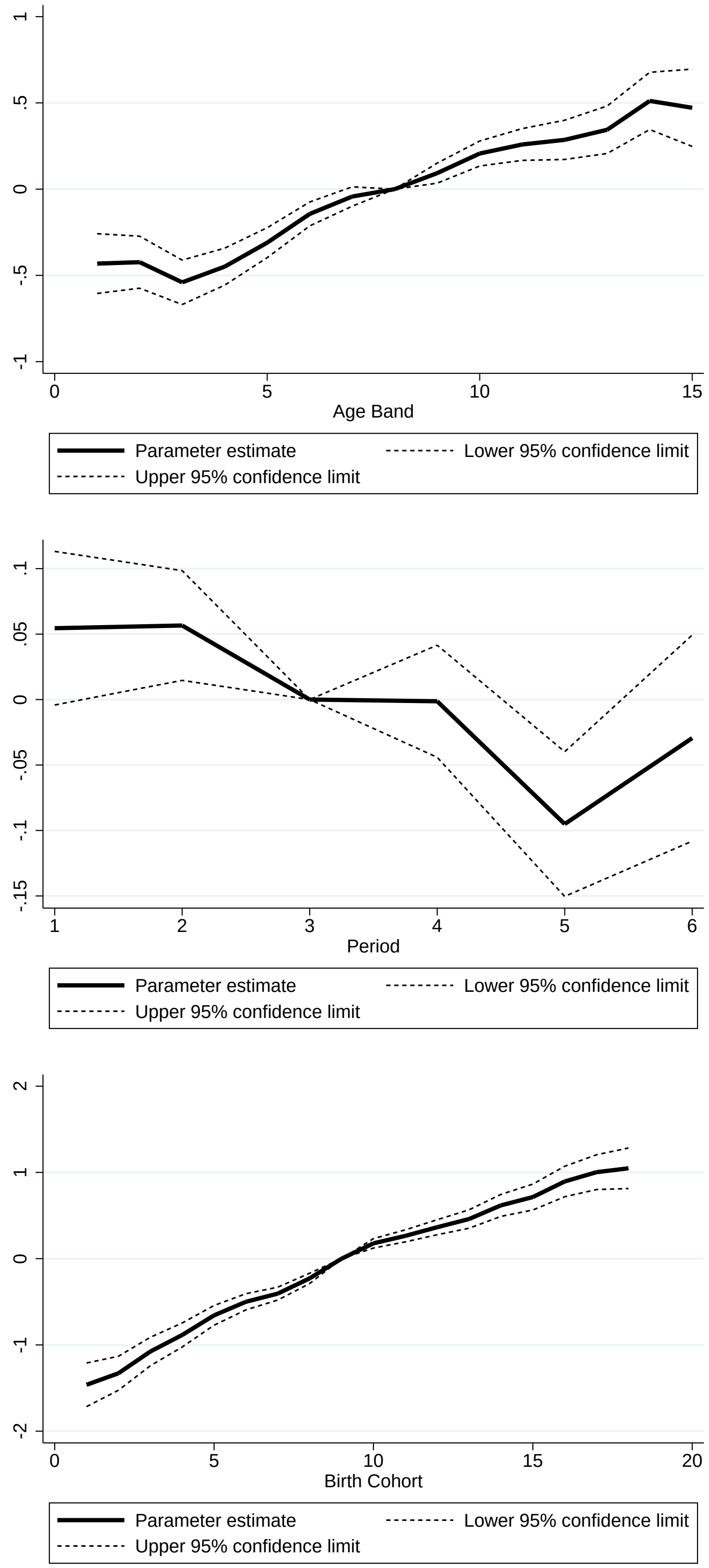
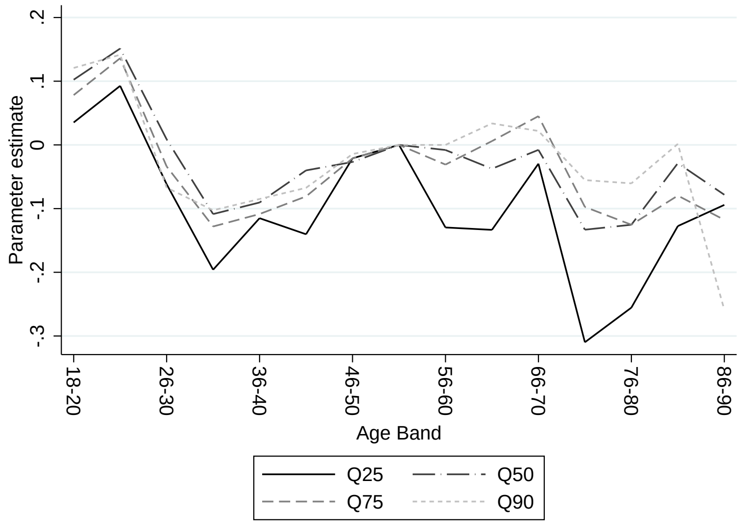
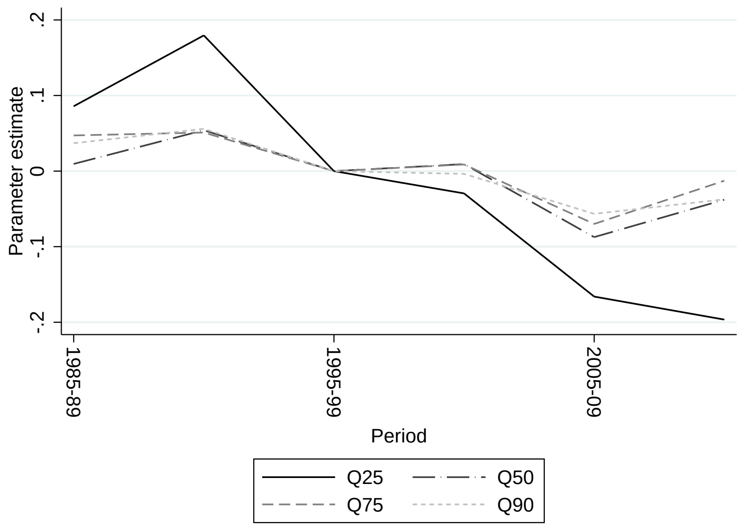


Figure 4.22: All Quantiles: Male





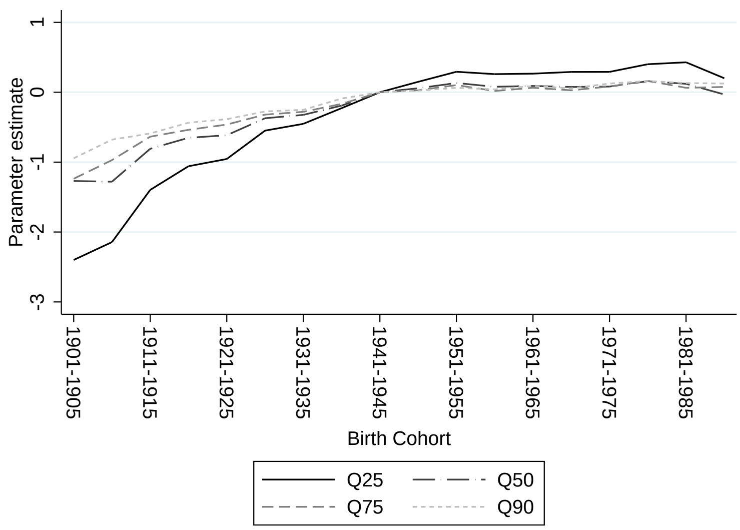
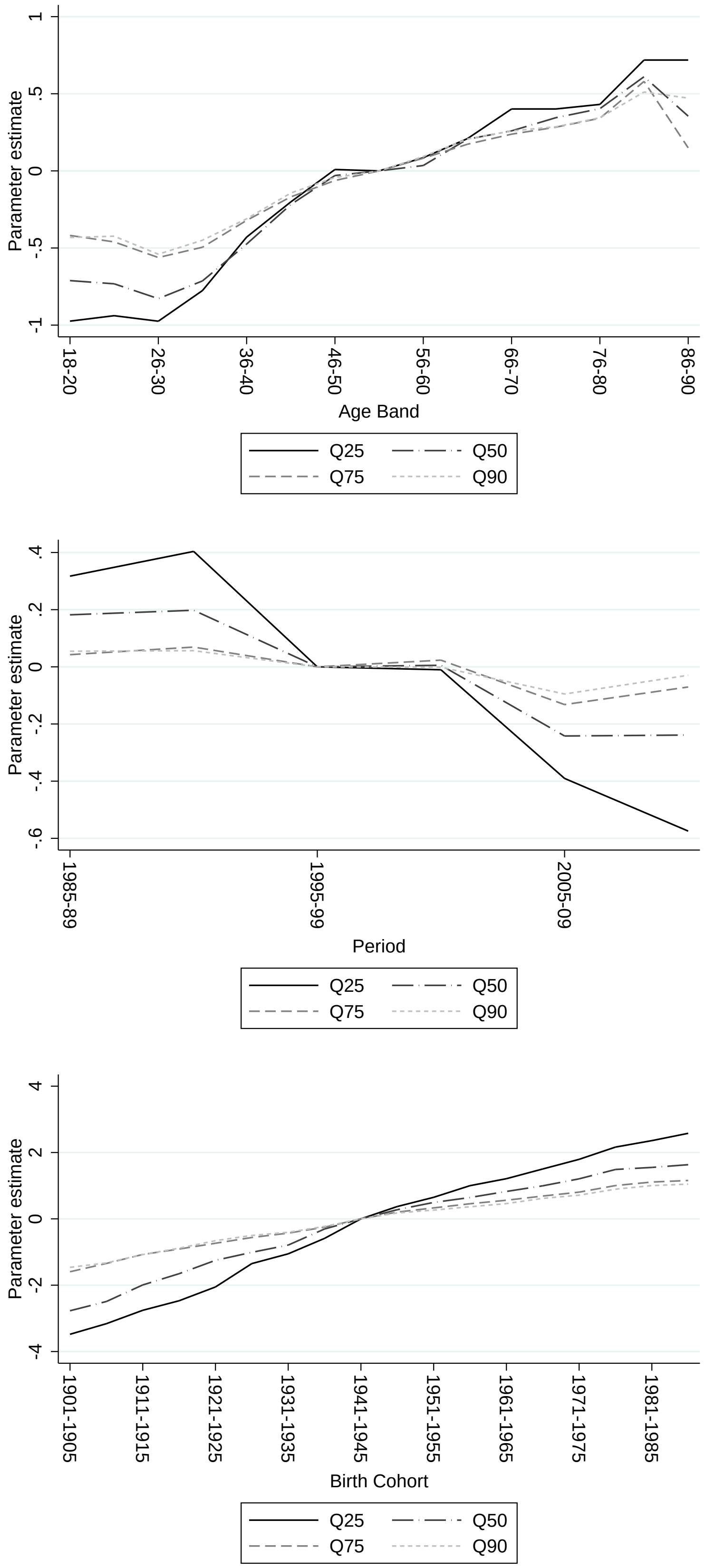


Figure 4.23: All Quantiles: Female



4.4.3 Age-Period-Price Results

The results presented in Table 4.12 show that the price of alcohol at age 18 is not very strongly related to the amount that a respondent drinks, even controlling for their age and the period. Furthermore, when price at 18 is statistically significant, it predicts that those who faced low alcohol prices at age 18 drink less than those who faced high alcohol prices at age 18. This is perhaps an odd result if one thinks that low price at 18 would encourage that cohort to drink more heavily, although it could be the case that they expect the price to rise in the future, and this then deters them from drinking heavily since they would build up consumption stock which would make them want to consume in the future. It is interesting to note that the positive coefficient on price at 18 is only significant in the heavier drinkers.

Table 4.12: Age-Period-Price Regression Results

	Mean	Q25	Q50	Q75	Q90
Age 18-20	0.427***	0.656***	0.299***	0.206***	0.210***
	(0.0285)	(0.0574)	(0.0304)	(0.0259)	(0.0291)
Age 21-25	0.337***	0.530***	0.235***	0.191***	0.205***
	(0.0246)	(0.0496)	(0.0262)	(0.0223)	(0.0251)
Age 26-30	0.130***	0.270***	0.0216	0.00903	-0.0203
	(0.0240)	(0.0484)	(0.0256)	(0.0218)	(0.0246)
Age 31-35	0.0522**	0.172***	-0.0639**	-0.0799***	-0.0920***
	(0.0237)	(0.0477)	(0.0252)	(0.0215)	(0.0242)
Age 36-40	0.0684***	0.237***	-0.0244	-0.0733***	-0.0754***
	(0.0234)	(0.0471)	(0.0249)	(0.0212)	(0.0239)
Age 41-45	0.0802***	0.227***	0.0190	-0.00415	-0.0296
	(0.0236)	(0.0475)	(0.0251)	(0.0214)	(0.0241)
Age 46-50	0.0852***	0.296***	0.0325	-0.00576	-0.00949
	(0.0247)	(0.0498)	(0.0263)	(0.0224)	(0.0253)
Age 56-60	-0.0727**	-0.142**	-0.0300	0.00191	-0.0303
	(0.0296)	(0.0596)	(0.0315)	(0.0269)	(0.0303)
Age 61-65	-0.0972***	-0.149**	-0.0644	0.0197	0.0532
	(0.0375)	(0.0755)	(0.0399)	(0.0340)	(0.0383)
Age 66-70	0.0853	0.190	0.0741	0.104	0.136
	(0.123)	(0.248)	(0.131)	(0.112)	(0.126)
Period 1985-1989	-0.0497***	-0.0615	-0.0366*	-0.0366**	0.0338*
	(0.0189)	(0.0381)	(0.0201)	(0.0172)	(0.0193)
Period 1990-1994	0.0707***	0.0720**	0.0327*	-0.00227	0.0348**
	(0.0171)	(0.0343)	(0.0182)	(0.0155)	(0.0174)
Period 2000-2004	0.100***	0.155***	0.0899***	0.0544***	0.0529***
	(0.0184)	(0.0371)	(0.0196)	(0.0167)	(0.0188)
Period 2005-2009	0.0186	0.0521	-0.00517	-0.00696	0.00544
	(0.0167)	(0.0336)	(0.0178)	(0.0152)	(0.0171)
Period 2010-2014	0.0565**	0.0227	0.0816***	0.117***	0.0891***
	(0.0239)	(0.0481)	(0.0254)	(0.0217)	(0.0244)
Log Real Price at 18	0.115*	0.179	0.0551	0.192***	0.153**
	(0.0691)	(0.139)	(0.0735)	(0.0626)	(0.0705)

Standard errors in parentheses. Observations: 177,493

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4.4 Rational Addiction Framework

Table 4.13 presents the results from a pseudo-panel regression. Here, each respondent is collapsed into a cell based on their birth cohort and sex, as is done in the pseudo-panel work of Meng (2014a). This is done to allow current consumption to depend on past and future consumption, as well as current price. However, instead of collapsing simply at the mean, the cell units are collapsed at differing quantiles of the distribution. Whilst this is not quantile regression, it does show how patterns change across the distribution in a similar manner.

The results show that past and future consumption are significant predictors of current consumption and the direction on the coefficients is as expected. However, the coefficient on price is positive and significant, which is perhaps unexpected.

Table 4.13: Rational Addiction Model - Collapsed at Quantiles

	Q25	Q50	Q75	Q90
Past Consumption	0.129**	0.230***	0.294***	0.331***
	(0.0602)	(0.0608)	(0.0599)	(0.0541)
Real Current Price	0.0292**	0.0384**	0.0133	-0.0772
	(0.0114)	(0.0192)	(0.0330)	(0.0518)
Future Consumption	0.160***	0.240***	0.278***	0.307***
	(0.0587)	(0.0581)	(0.0561)	(0.0534)
Constant	-1.381	-0.129	5.532	18.68***
	(1.191)	(2.038)	(3.591)	(5.791)

Standard errors in parentheses. Observations: 308
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5 Conclusions

This chapter has examined changes in alcohol consumption across age, period and birth cohort, but also extended the analysis to look at quantiles of the distribution instead of mean consumption or proportions belonging to a consumption 'type' as Kemm (2003) did. It has found that younger age cohorts, especially females, have tended to drink more than their older counterparts, although this trend appears to have stopped with the youngest few cohorts. There is also a different age effect by cohort, with the upper quartile of women born in the 1950s expected to drink more as they age compared to women born in 1970 who are expected to drink less as they age.

The extension of the work done by Meng et al (2014a) has found largely similar results across all quantiles. As shown in Figure 4.22 and Figure 4.23, the effects are larger in the lower quantiles. For example, it appears that there has been convergence in the drinking distribution across successive birth cohorts, once age effects and time period are controlled for. However the opposite is true for time period, with notable divergence over time once cohort and age effects are controlled for. This might highlight the limitation of age-period-cohort analysis, especially when viewing the predicted age effect for the lower quartile of male drinkers.

The rational addiction model is supported insofar that previous and future consumption are significant predictors of current consumption. The price when a birth cohort turns 18 has a significant, positive effect on consumption, and this is especially true in the top end of the drinking distribution. It may be that those facing high prices at 18 expect prices to rise in the future and this deters them from drinking heavily, since they would be affected most if the price were to rise due to consumption stock. The current price appears to have a small, significant, positive effect on current consumption, which is a puzzling finding.

A limitation to this work is that the long-run price of alcohol, as shown in Figure 4.1, has not seen considerable change save for a period of low relative price between 1972 and 1980, which is more likely due to high inflation during that period causing an artificial decrease in the (real terms) price of alcohol. However, as seen in this thesis, there has been a change in the relative price of on- and off-premise alcohol, with the price of off-premise alcohol - which is typically cheaper - falling considerably. This means that the price *any form of alcohol* has fallen, and is being masked by increasing on-premise prices.

The purpose of this chapter was to examine changes in drinking patterns over the life-course and across the drinking distribution, the latter of which is the major contribution to the literature. The results presented have described a picture of some polarisation between abstention and consumption, but convergence within quantiles of the drinking distribution over time. That is, the proportional change in consumption in the top end of the distribution has been less than in the bottom end of the distribution. This also fits in with the findings presented in Chapter 2. The results also show that price at the age of 18 is not a good predictor of how much people drink later in life compared to other cohorts, and that this is true across the drinking distribution. This is also found in the rational addiction framework.

For policymakers this is interesting. Firstly, it shows that in the long run price has had little effect in determining consumption. Secondly, it shows that increasing consumption has been seen across successive birth cohorts and across the drinking distribution, suggesting a possible change in culture over time.

4.5.1 Future Research

Future research could focus on the alcohol duty escalator, which obliged governments to increase alcohol taxation above inflation. The legislation was set out in 2008, although it was scrapped in the 2014 budget. Analysis of alcohol consumption, especially of those who became 18 under the duty escalator, would be of interest because the future price of alcohol is expected to increase consistently. People may be reluctant to drink heavily knowing that prices are going to increase in the future, and this is especially true for those turning 18 who (are assumed to) have no consumption stock requiring them to drink heavily. Similarly, the effect of the tobacco duty escalator could be analysed in the context of rational addiction.

Another avenue for potential future work is to look at how mortality has affected the lifecourse trajectories, and how this affects age-period-cohort modelling. If heavier drinkers are more likely to die prematurely, then this biases downwards the trend of the lifecourse. Ideally, panel data would be needed to examine this in detail.

This paper has used price at the age of 18 in place of cohort effects to remove the colinearity problem. However, one could also use unemployment or GDP (or some other potential cohort indicator). It is also possible to use these factors instead of period effects, since the literature suggests that these factors - as well as price - affect current alcohol consumption (see, for example, the work by Luoto et al (1998)).

Finally, future work could look at using reduced-form analysis to model the effect of the price of alcohol during adolescence and future health outcomes.

Chapter 5

Concluding Remarks

This thesis has presented three distinct chapters on the economics alcohol, albeit with a unifying theme which is to extend the existing literature by looking at the distribution of alcohol and the effects of policy on the distribution.

Chapter Two used quantile regression to estimate the price elasticity of demand for alcohol across the drinking distribution. It found that heavy drinkers are less responsive to price than lighter drinkers, that this is true regardless of whether one uses conditional or unconditional quantile regression, and that heavier drinkers absorb price increases by switching to lower quality alcohol. It has extended the literature in several ways including the comparison of conditional and unconditional quantile regression to estimate the price elasticity of demand for alcohol, the construction of region-time-specific prices using unit values, and the analysis of quality substitution across the drinking distribution.

Chapter Three compared different methods for calculating a price elasticity of demand for alcohol when there are multiple zeros in the dependent variable, and these zeros arise for three separate reasons - abstention, corner solutions, and infrequent purchase. It found that the much-used Tobit model generated much larger estimates of the price elasticity of demand for alcohol, which is likely to be caused by the inherent assumption in the Tobit that the direction of the coefficients in both the participation and consumption decision are the same. The double-hurdle model relaxes this assumption, and also imposes a second hurdle which allows for a difference between abstention and corner solutions which the Tobit model does not allow. The chapter extends the literature by using a novel predictor of abstention (pork expenditure and gambling expenditure), and through the use of the same region-time-specific prices as the first chapter.

Chapter Four extended existing analysis of trends in alcohol consumption across age, period and birth cohort, as well as empirically testing the theory of rational addiction, across the drinking distribution. It found that there were significant differences in alcohol consumption across age, period and cohort. Whilst there were differences, the pattern appears similar across the quantiles of the drinking distribution. No evidence was found that the price at 18 plays a negative role in whether members of a birth cohort begin drinking heavily, although the theory of rational addiction may suggest that forward-looking consumers may predict that future prices would increase and this may deter them from beginning to drink heavily whilst the price is low. Past and future consumption are found to be significant predictors of future consumption.

Overall, then, this thesis has extended the literature on alcohol in two ways. Firstly, it has extended the analysis from simply looking at the mean of the distribution. The work on quantile regression in Chapter 2 showed how the heaviest drinkers had the lowest price elasticity of quantity demanded, yet the highest price elasticity of quality demanded. Chapter 4 showed that successive birth cohorts have increased alcohol consumption across the distribution, and showed how the price at 18 was not a good predictor of alcohol consumption across the drinking distibution. Secondly, this thesis has shown how important non-consumption, and how non-consumption is handled, is. Chapter 3 tested different methods of estimating the price elasticity of demand when non-purchasers form a large proportion of a dependent variable and found that the standard Tobit model finds much larger elasticities than any other method. Chapter 4 showed that abstention is increasing over time and birth cohorts, whilst conditional consumption is increasing, further highlighting why the Tobit model might be insufficient.

Chapter 6

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Chapter 7

Appendices

Appendix A - Ethics Clearance

This project was approved by the Faculty of Health and Medicine Research Ethics Committee, and a statement confirming this is shown on the following page.

LANCASTER
UNIVERSITY

Applicant: Robert Pryce
Supervisor: Prof Bruce Hollingsworth
Department: DHR

12 May 2014

Dear Robert and Bruce,

Re: The economics of alcohol

Thank you for submitting your research ethics application for the above project for review by the Faculty of Health and Medicine Research Ethics Committee (FHMREC). The application was recommended for approval by FHMREC, and on behalf of the Chair of the University Research Ethics Committee (UREC), I can confirm that approval has been granted for this research project.

As principal investigator your responsibilities include:

- ensuring that (where applicable) all the necessary legal and regulatory requirements in order to conduct the research are met, and the necessary licenses and approvals have been obtained;
- reporting any ethics-related issues that occur during the course of the research or arising from the research to the Research Ethics Officer (e.g. unforeseen ethical issues, complaints about the conduct of the research, adverse reactions such as extreme distress);
- submitting details of proposed substantive amendments to the protocol to the Research Ethics Officer for approval.

Please contact the Research Ethics Officer, Debbie Knight (01542 592605 ethics@lancaster.ac.uk) if you have any queries or require further information.

Yours sincerely,

S.C. Taylor

Sarah Taylor
Secretary, University Research Ethics Committee

Cc Fiona Aiken, University Secretary, (Chair, UREC); Professor Paul Bates (Chair, FHMREC)

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Appendix B - Simulation: Selection by Dependent Variable

This appendix demonstrates through simulation how endogenously splitting the sample based on the dependent variable produces biased estimates.

Firstly, two independent variables - x_1 and x_2 - are created for 1 million observations (denoted with subscript i). These are random observations from normal distributions and are modelled exactly the same.

$$\begin{aligned} x_1 i &\sim N(100, 20) \\ x_2 i &\sim N(100, 20) \end{aligned} \tag{7.1}$$

A simple pairwise correlation reveals there is no correlation between the two variables, as would be expected. Secondly, a dependent variable Y is created. This is a linear combination of the two independent variables, plus a constant and a normally-distributed error term.

$$\begin{aligned} c_i &\sim N(20, 2) \\ e_i &\sim N(0, 10) \\ \beta_1 &= \beta_2 = 1.5 \\ Y_i &= c_i + \beta_1 x_1 i + \beta_2 x_2 i + e_i \end{aligned} \tag{7.2}$$

The scatterplots of Y_i and x_1 and x_2 are shown in Figure 7.1. Regressing Y_i against $x_1 i$ and $x_2 i$ using OLS shows that the correct estimates of β_1 and β_2 are obtained. Quantile regression, based on 3 equal quantiles, also obtains the correct estimates for β_1 and β_2. This is shown in Table 7.1. The bias occurs most in the middle third of the distribution, since this experiences the most truncation. The bias due to selection on the dependent variable becomes more pronounced as the number of endogenously-selected subgroups increases, since more truncation occurs.

Figure 7.1: Scatterplot of Y against x_1 and x_2

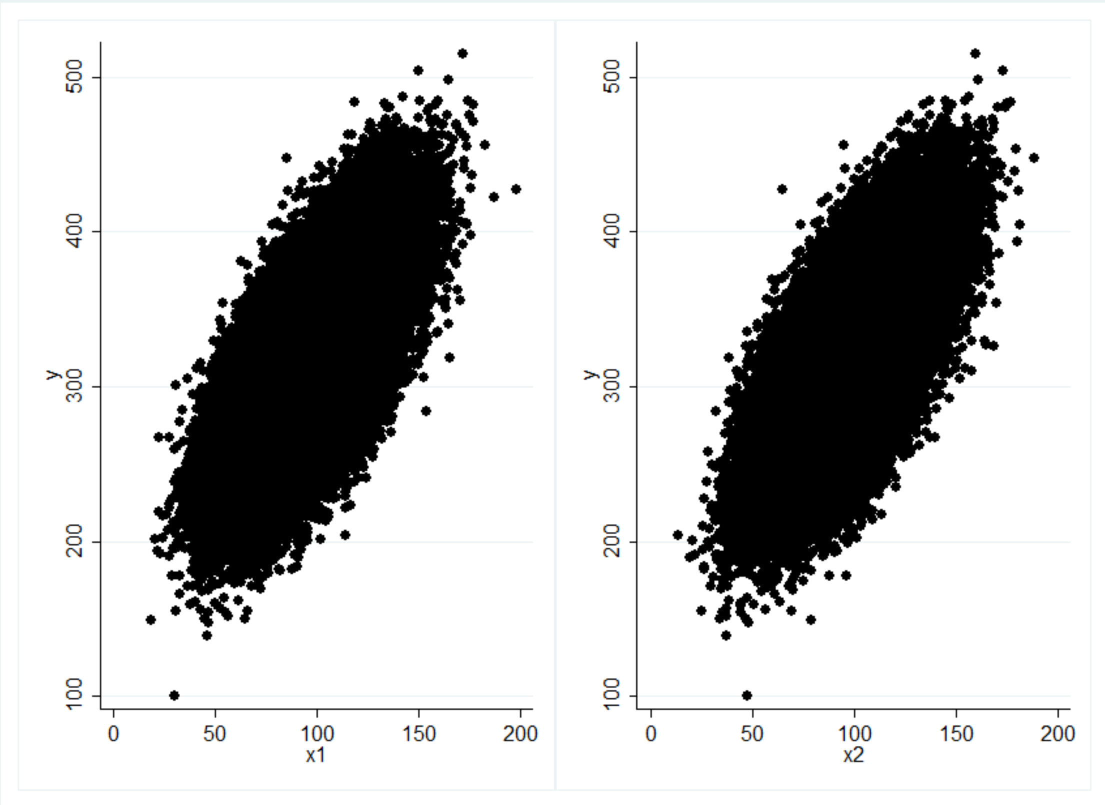

Table 7.1: Comparison of Estimated Coefficients

	Quantile			Selection		
	Q1	Q2	Q3	Q1	Q2	Q3
x1	1.498	1.498	1.502	1.318	0.802	1.316
	(0.002)***	(0.002)***	(0.002)***	(0.004)***	(0.005)***	(0.004)***
x2	1.501	1.501	1.499	1.321	0.804	1.311
	(0.002)***	(0.002)***	(0.002)***	(0.004)***	(0.005)***	(0.004)***
_cons	10.182	20.065	29.801	48.035	159.265	65.442
	(0.344)***	(0.284)***	(0.347)***	(0.559)***	(0.863)***	(0.755)***

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$